Method for assessing quality of the variogram

by H.J. Glass*

Synopsis

Collection, preparation, and analysis of blasthole chippings is expensive. Frequently, interpolation of grades at unsampled locations is considered using techniques like kriging. A pre-requisite for kriging is that an experimental variogram is established. In order to assess the quality of the experimental variogram, a measure is developed in this paper. The measure is derived from analysis of the time-honoured expression relating the variance, semivariance, and covariance. It reflects the weighted average deviation of the summed semivariance and covariance from the biased variance. The proposed measure allows assessment of the influence of key variables on the quality of the variogram. Using simulated data, it follows that the quality improves with an increasing number of samples, increasing density of the sampled locations, increasing regularity of the sampling pattern, and increasing uniformity of grades in the absence of correlation. Application to real data shows that the minimum number of samples could coincide with a marked decrease in the value of the measure. Establishing a threshold value is subject to further research.
Keywords: variogram, variance, covariance, semivariance, minimization, sampling.

Introduction

Although samples are routinely collected during blasthole drilling, it is necessary to optimize the number of samples which are prepared and analysed. This can be achieved by estimating sample grades using geostatistical techniques such as kriging. For this purpose, measured sample grades are processed to produce a variogram, in which the semivariance or covariance are plotted versus the distance between pairs of measured datapoints. The points of the experimental variogram, often determined independently in several directions, are fitted with an empirical expression known as a theoretical variogram. Using the theoretical variogram, the unknown sample grade is estimated from a combination of weighted measured grades.

The quality of the experimental variogram is generally judged by the shape of the variogram or by the goodness-of-fit between the experimental and theoretical variograms. Neither measure for the quality is necessarily reliable. Hence, an alternative, quantitative measure is developed which links the quality of the variogram to the number of samples per unit volume of ore. This allows assessment whether additional preparation and analysis of samples is required. In this way, the minimum number of samples for applying geostatistics is identified.

The measure for the quality of the variogram is developed by considering the validity of a well-known equation stating that the variance, $Var\{x\}$, is equal to the sum of the semivariance (γ_{ij}) and the covariance $(Cov\{x_i x_j\})$:

$$Var\{x\} = \gamma_{ij} + Cov\{x_i x_j\} \qquad [1]$$

where x represents the grade and i and j are indices of arbitrary datapoints. Properties and application of the measure are demonstrated using simulations and real data.

Variogram

The semivariance and the covariance are well-established measures for characterizing the correlation between grades measured at different locations in an orebody. The significance of the trend in either measure is opposite: within a certain range, the correlation increases for lower semivariances and for higher covariances. Figure 1 shows a theoretical plot of the semivariance and covariance as a function of the distance between datapoints. Note that a difference can exist between the theoretical variogram and the experimental points it is based on.

Three regions of the variogram are distinguished: (i) the origin, which relates to a zero distance between the datapoints, (ii) the region where the distance between the datapoints is within the range, and (iii) the

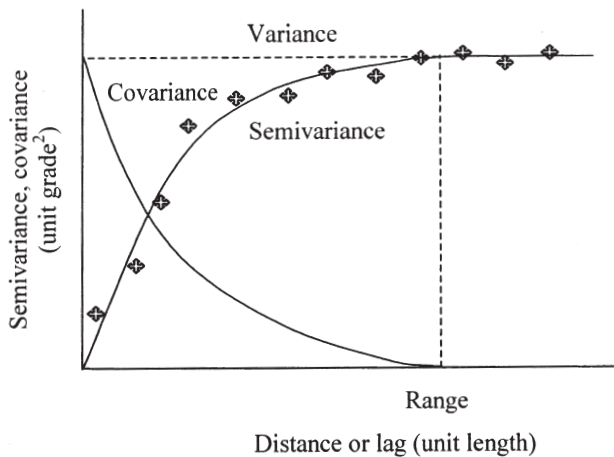# Method for assessing quality of the variogram

Figure 1—Typical theoretical variogram for an orebody, based on points of the experimental semivariogram (γ)

region where the distance between the datapoints is larger than the range. For each region, the validity of Equation [1] is analysed using the definitions of the various variances.

Definition of variance

The variance of a set of grades, $Var\{x\}$, is given by:

$$Var\{x\} = \frac{1}{N-1} \sum_{i=1}^{N} (x_i - \bar{x})^2 \qquad [2]$$

where x_i is an arbitrary grade, $\bar{x}$ is the average grade, and N is the number of grades in the set. Equation [2] provides an unbiased estimate of the variance. A common alternative definition divides the summed squared differences by N rather than by N-1. This definition, which allows for a variance based on single datapoint, provides a biased estimate of the variance.

The covariance, $Cov\{x_ix_j\}$, between grades measured at unique pairs of different locations i and j is given by:

$$Cov\{x_ix_j\} = \frac{1}{m} \sum_{i=1}^{N} \sum_{j=i+1}^{N} (x_i - \bar{x})(x_j - \bar{x}) \qquad [3]$$

where m is the number of pairs. Note that the number of pairs, m, is related to the number of grades or datapoints, N, as follows: $m = \frac{N(N-1)}{2}$. It is also possible to define the covariance with all possible pairs of locations, including pairing of the datapoint to itself. In that case, the summation of j starts at 1 and the number of pairs, m, will equal N^2. Because the pairing of a datapoint to itself does not necessarily have a zero covariance, either definition is likely to produce different values.

Finally, the semivariance, γ_{ij}, for unique pairs of grades measured at different locations is given by:

$$\gamma_{ij} = \sum_{i=1}^{N} \sum_{j=i+1}^{N} (x_i - x_j)^2 \qquad [4]$$

As with the covariance, the semivariance could be defined for all possible pairs of locations, including the pairing of the datapoint to itself. This is likely to lead to different values of the semivariance: although the semivariance of a datapoint

paired to itself is zero, it counts as a pair and hence lowers the semivariance.

Comparison of Equations [2] to [4] reveals that $Var\{x\}$, $Cov\{x_ix_j\}$, and γ_{ij} are all zero when the grade is constant, i.e. $x_i = x_j = \bar{x}$ for every i and j. This constitutes a very rare type of orebody where a single sample (N=1) would suffice. In the following subsections, the validity of Equation [1] is examined for non-zero variances.

Beyond the range

When the distance between datapoints exceeds the range (see Figure 1), spatial correlation between the datapoints is absent, i.e. the grade varies independently of the sampled location. This corresponds to random variation of the grade with the distance. For convenience, we consider random variation irrespective of the distance. When the range becomes negligible, all distances between any pair of different datapoints exceeds the range. According to Figure 1, the variance should equal the semivariance beyond the range. Writing the variance out in full leads to:

$$Var\{x\} = \frac{1}{N-1} \sum_{i=1}^{N} \left(x_i^2 - 2x_i\bar{x} + \bar{x}^2 \right)$$

$$= \frac{1}{N-1} \left(\sum_{i=1}^{N} x_i^2 - \frac{1}{N} \left(\sum_{i=1}^{N} x_i \right)^2 \right) \qquad [5]$$

Recognizing that $\sum_{i=1}^{N} \sum_{j=i+1}^{N} (x_i^2 + x_j^2)$ equals $(N-1) \sum_{i=1}^{N} x_i^2$, the semivariance is written as follows:

$$\gamma_{ij} = \frac{1}{N} \sum_{i=1}^{N} x_i^2 - \frac{2}{N(N-1)} \sum_{i=1}^{N} \sum_{j=i+1}^{N} (x_ix_j) \qquad [6]$$

Combining Equations [5] and [6] and simplifying leads to:

$$\left(\sum_{i=1}^{N} x_i \right)^2 - \sum_{i=1}^{N} x_i^2 = 2 \sum_{i=1}^{N} \sum_{j=i+1}^{N} (x_ix_j) \qquad [7]$$

Note that Equation [7] is valid for any value of x. Given that the semivariance equals the variance, Equation [1] prescribes that the covariance should be zero. However, this is not the case. Instead, the summed semi- and covariance equal an expression for the biased variance, given by:

$$Var\{x\} = \frac{1}{N} \sum_{i=1}^{N} (x_i - \bar{x})^2 = \frac{1}{N} \sum_{i=1}^{N} x_i^2 - \bar{x}^2 \qquad [8]$$

The sought equality follows by rewriting the covariance. Considering all unique pairs of different datapoints:

$$Cov\{x_ix_j\} = \frac{2}{(N-1)N} \sum_{i=1}^{N} \sum_{j=i+1}^{N} (x_i - x_j) - \bar{x}^2 \qquad [9]$$

Using Equations [6], [8], and [9] to substitute the terms in Equation [1]:

$$\frac{1}{N} \sum_{i=1}^{N} x_i^2 - \bar{x}^2 = \frac{1}{N} \sum_{i=1}^{N} x_i^2 - \frac{2}{N(N-1)}$$

$$\left(\sum_{i=1}^{N} \sum_{j=i+1}^{N} (x_ix_j) - \sum_{i=1}^{N} \sum_{j=i+1}^{N} (x_ix_j) \right) - \bar{x}^2 \qquad [10]$$

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Equation [10] confirms that the biased variance equals the summed semi- and covariance for any value of x. This equality is also true when invoking the alternative definitions for semi- and covariance, where $m = N^2$ and $\sum_{i=1}^{N} \sum_{j=i=1}^{} (x_i^2 + x_j^2) = 2N \sum_{i=1}^{N} x_i^2$. Relations between the variances are summarized in Figure 2.

The bias, expressed as a fraction of the variance, is inversely proportional to the number of datapoints, N. Although this implies that bias becomes insignificant for larger numbers of datapoints, it may play a role when minimizing the number of samples.

At the origin

Figure 1 suggests that the semivariance at the origin is zero and the covariance equals the variance. However, Equations [2] and [3] preclude pairs of grades with a zero distance. Therefore, the alternative definition of semivariance is required which allows for all possible pairs of datapoints including pairs of a single datapoint. Similarly, the alternative definition of covariance at the origin coincides with the biased variance, given by Equation [8].

Inside the range

Inside the range, the semivariance and the covariance vary with the distance between datapoints (see Figure 1). Knowledge of the trend in the semivariance or the covariance is required because the semivariance or covariance influence the weighting of measured grades used for interpolation. The trends in the semi- and covariance are monitored by defining intervals for classifying the distance between pairs of datapoints. This implies that datapoints are selectively paired. Subsequently, the grades of selected pairs are processed to provide a global experimental variogram. When also taking the relative orientation of paired datapoints into account, directional variograms can be constructed.

It has been shown previously that, for all possible pairs of datapoints, the summed semi- and covariance equal the biased variance. With selective pairing, there is no guarantee that this applies for each interval in every direction: the

datapoints may be unequally represented in the pairings due to the spatial distribution of the datapoints (Figure 3). Given variable grades, the simplified expressions for the semivariance and the covariance, given by Equations [6] and [9], is erroneous. The error will depend, among other aspects, on the distribution of the grades and is expected to decrease with increasing numbers of samples.

The objective is to characterize the deviation between the summed semi- and covariances and the variance. For this purpose, the definition of unbiased variance, rather than biased variance, is used so that the deviation takes bias into account. By rewriting and normalizing Equation [1], we obtain the following measure χ:

$$\chi = \left| 1 - \frac{\gamma_{ij} + Cov\{x_i x_j\}}{Var\{x\}} \right| \qquad [11]$$

While χ relates to a single interval, an average value of χ for all intervals relates to the quality of the entire variogram. In practice, χ is expected to decrease with increasing numbers of pairs. Because the number of pairs in each interval is variable, values of χ will be weighted with the fraction of pairs in the corresponding interval. Hence, we propose to infer the quality of the variogram from the weighted average value of χ, denoted $\bar{\chi}$. In equation:

$$\bar{\chi} = \frac{1}{\sum_{l=1}^{T} m_l} \sum_{k=1}^{T} \left(\left| 1 - \frac{\left(\gamma_{ij} + Cov\{x_i x_j\} \right)_k}{Var\{x\}} \right| m_k \right) \qquad [12]$$

where T is the number of intervals. Equation [12] is suitable for application during the initial stage of a sampling campaign. Once the initial samples grades have been determined, the value of $\bar{\chi}$ can be computed and compared to a predetermined threshold value. Additional samples are drawn until the actual $\bar{\chi}$ sinks below the threshold value for $\bar{\chi}$. This corresponds to the minimum number of samples required to produce a variogram of prescribed quality. In the following, properties of the proposed measure are illustrated.
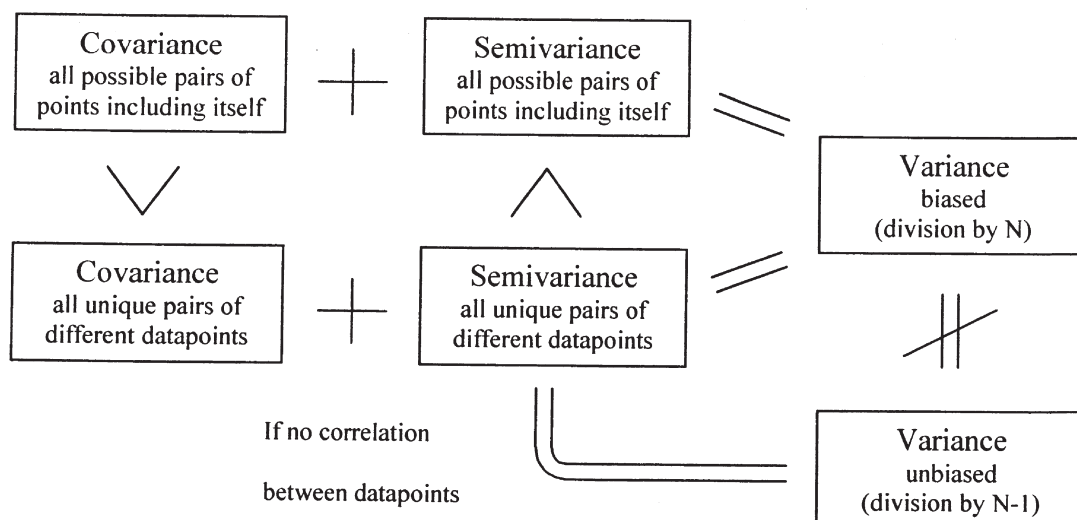

Figure 2—Relations between the various variances

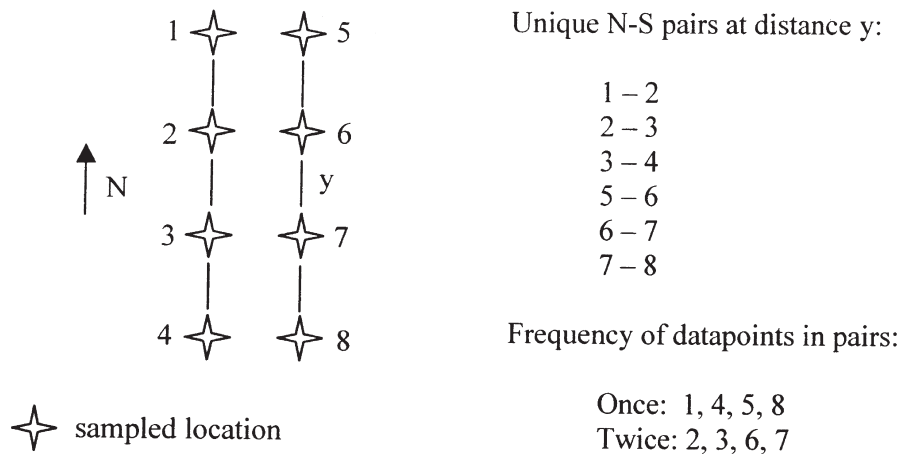# Method for assessing quality of the variogram

Unique N-S pairs at distance y:

1 – 2
2 – 3
3 – 4
5 – 6
6 – 7
7 – 8

Frequency of datapoints in pairs:

Once: 1, 4, 5, 8
Twice: 2, 3, 6, 7

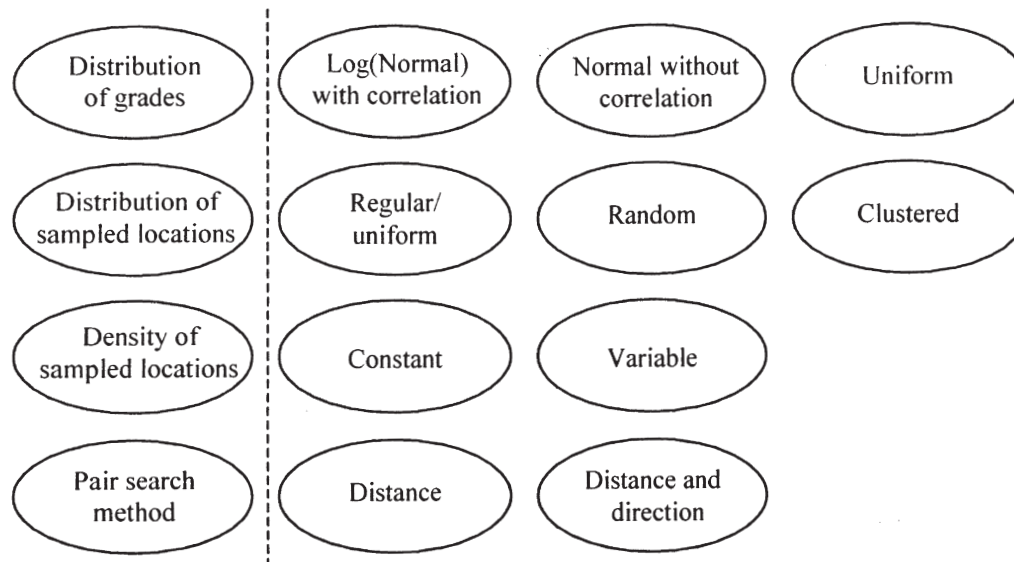Figure 3—Selective pairing influences the semivariance and covariance

Figure 4—Factors influencing the quality of the variogram

Properties

Values of the proposed measure will depend on the distribution of grades, the spatial distribution of the sampled locations, and the method used to form pairs of datapoints. Figure 4 summarizes the factors which are considered in the following subsections.

Distributions of grades

Both artificial and measured data were used to determine properties of $\bar{\chi}$. Two types of artificial data were generated using random numbers: sets of grades sampled from a uniform distribution and sets of grades sampled from a normal distribution. These grades were assigned to patterns

of sampled locations. It should be noted that spatial correlation is absent in both types of sets. As a result, the range will be negligible, giving the variogram its common name: the nugget variogram[2]. Examples of both types of distribution are shown in Figure 5.

Measured data were obtained from the Lerokis barite-gold and silver deposit on the island of Wetar in Indonesia. The mineralization is dispersed in laterized breccia units which contain barite. In order to establish a drilling pattern prior to mining operations, samples were drawn on a regular 5 m by 5 m, approximately rectangular, grid. Using a 100 mm reverse circulation drill with air as a coolant and medium, about 20 kg of drillhole chippings were collected from each sampled location. In total, 240 samples were
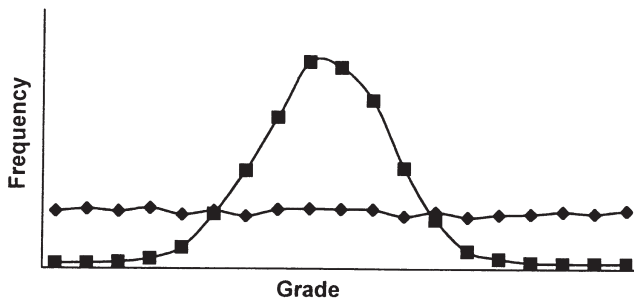
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Figure 5—Distribution of grades obtained by sampling uniform and normal distributions using random numbers
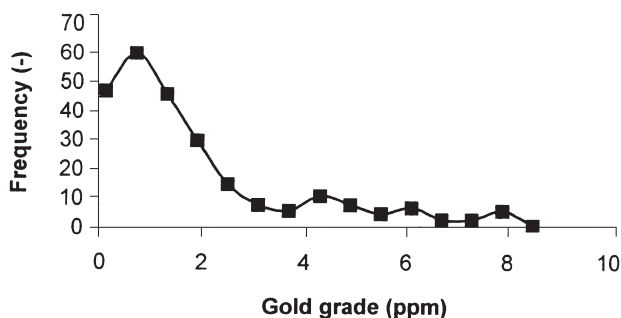

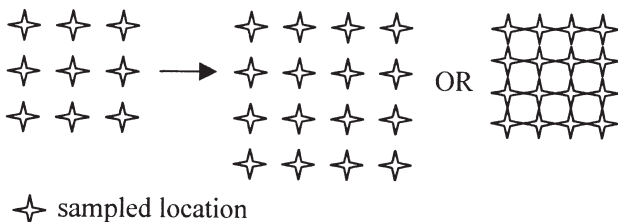**Figure 6—Frequency of grades in samples drawn from a barite-gold deposit**

Figure 7—Evolution of constant-density (middle) and constant-size (right) regular grids

analysed. The average grade and variance were 2.07 ppm and 3.51 ppm² of gold respectively. The frequency distribution of the grades is shown in Figure 6.

Distribution and density

Three types of spatial distributions are generally distinguished[2]: regular and uniform distributions, clustered distributions, and random distributions. A regular grid covering an area may consist of samples drawn at the corners of triangles, squares, or hexagons. Two types of regular grids were used: a square grid with a constant distance between sampled locations, and a square grid of a constant size. Figure 7 shows that the development of the density, defined as the number of sampled locations per unit area, differs for either type of grid.

Depending on the sampling strategy, either type of regular grid could serve to establish whether further sampling is required. In practice, a completely regular grid is rare because it is unlikely that geological features would be

ignored. The presence of features such as outcrops could lead to differences in the density of sampled locations. If only outcrops are sampled, a clustered distribution could readily be observed. Two types of clustered distributions were constructed: a constant number of datapoints per cluster— variable number of cluster types and a constant cluster density—variable number of cluster types (Figure 8). For more datapoints per cluster than shown in Figure 8, the sampled area was enlarged to ensure that the intercluster distance always exceeded the maximum intracluster distance.

In practice, the distribution of sampled locations is likely to be irregular in addition to regular and clustered sections. This could be classified as a random distribution. Using random numbers, these were constructed within an area of a fixed size.

Results of simulations

Grades drawn at random from a uniform distribution were assigned in a regular pattern with a constant density (see Figure 7). Pairs were classified in intervals defined as multiples of the closest distance between adjacent sampled locations and extending in every direction. For selected numbers of samples, the value $\bar{\chi}$ was determined 4000 to 8000 times. This number of simulations was sufficient to ensure stable values of $\bar{\chi}$. Average values of $\bar{\chi}$ for each grid size are plotted in Figure 9.

The simulated curve in Figure 9 suggests that the quality of the variogram initially improves rapidly, with the benefit due to additional samples becoming progressively smaller. Hence, further analysis will focus on the region up to 100 samples. Figure 9 also features a baseline representing the lowest possible curve. This curve is obtained when all pairs of datapoints fall inside a single interval, indicating the highest possible density of sampled locations. The baseline is expressed by the equation $\bar{\chi}=1/N$. This constitutes the relative difference between the biased variance, which satisfies Equation [1], and the unbiased variance, on which the definition of $\bar{\chi}$ is based. Hence, the quality of the semivariogram is partly determined by the definition of the measure itself.

Given the difference between the simulated curve and the baseline, the effect of the density of sampled locations is examined. When sampling on a square area of fixed size, the density can be varied by changing the width of intervals used for establishing pairs of datapoints. Figure 10 shows the trends when the edge length of the square area is unity. Note that an interval width of 3 ensures that all pairs are classified in a single interval, making the corresponding curve coincide with the baseline.

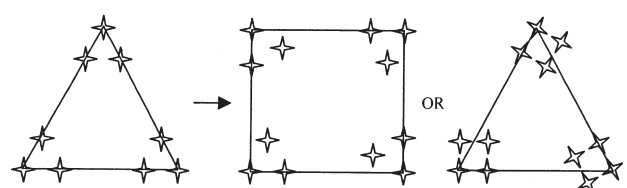In many cases, the density of sampled locations may vary

Figure 8—Evolution of clustered distributions, with a constant number of points per cluster (middle) or constant number of clusters (right)

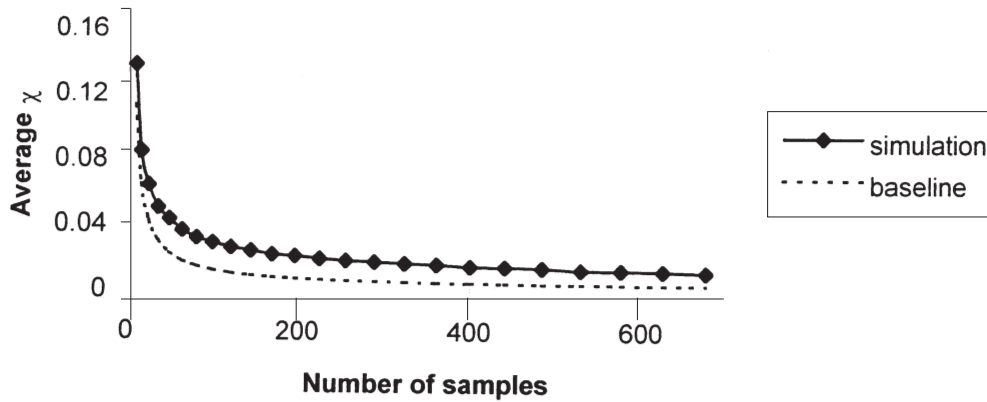# Method for assessing quality of the variogram

Figure 9—Effect of the number of samples given a uniform grade distribution on a regular grid
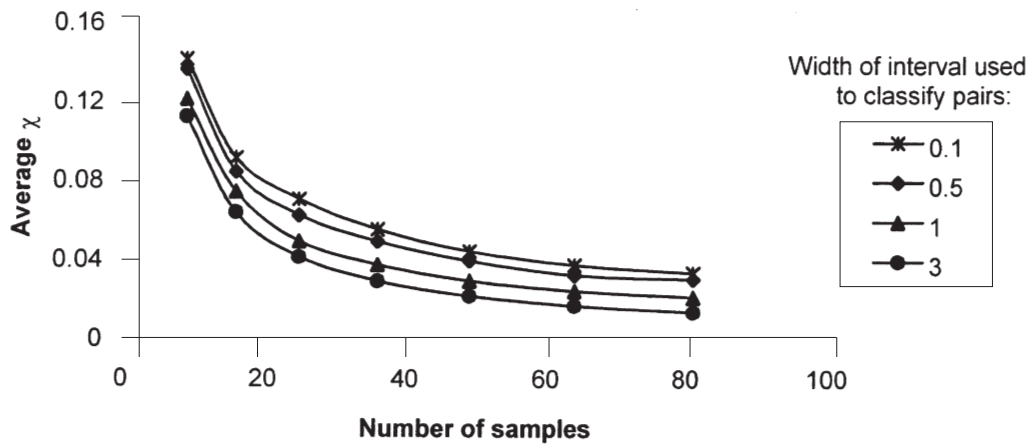

Figure 10—Effect of the density of sampled locations given a uniform grade distribution on a regular grid. The interval width is relative to the edge length of the sampling pattern
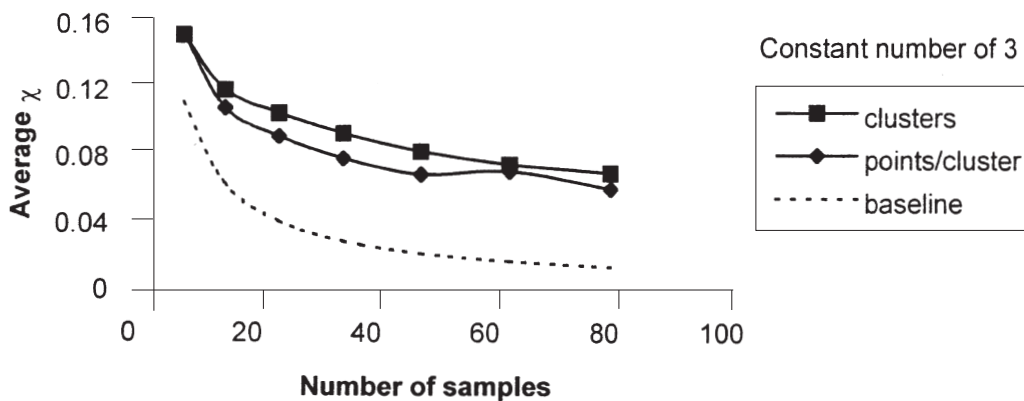

Figure 11—Effect of clustered datapoints given a uniform grade distribution

locally, leading to clustered distributions. With intervals defined as multiples of the distance between adjacent datapoints in a cluster, the number of intervals containing pairs greatly increases. Because this corresponds to a very low density, the average value of $\bar{\chi}$ will increase significantly. Simulations for two types of clusters (see Figure 8) confirm that clustered distributions are detrimental for the quality of

the variogram. Figure 11 shows that a large number of small clusters are better than a few large clusters. In the limiting case, the former would correspond to a regular distribution. The slight increase in $\bar{\chi}$ observed above 60 samples is probably related to the construction of the clusters. Similar anomalies were observed when performing simulations with clusters containing more datapoints.
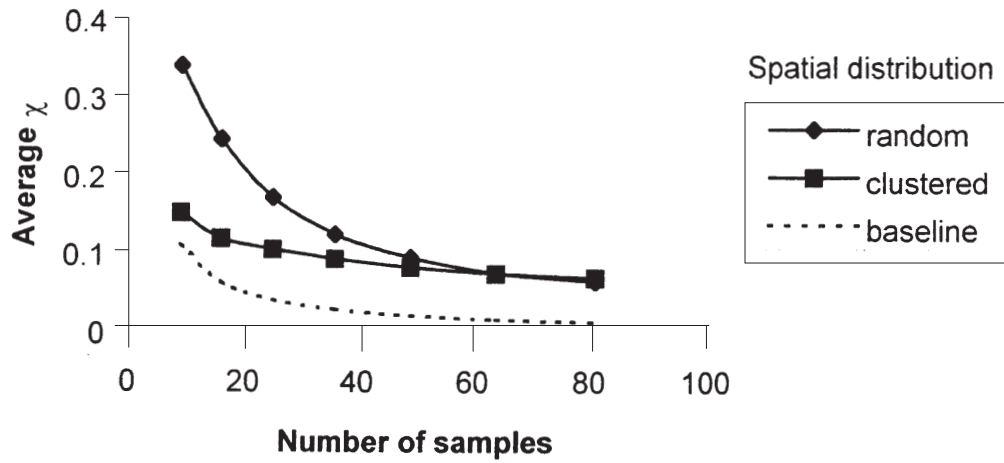
Figure 12—Effect of random and clustered distributions of sampled locations given a uniform grade distribution
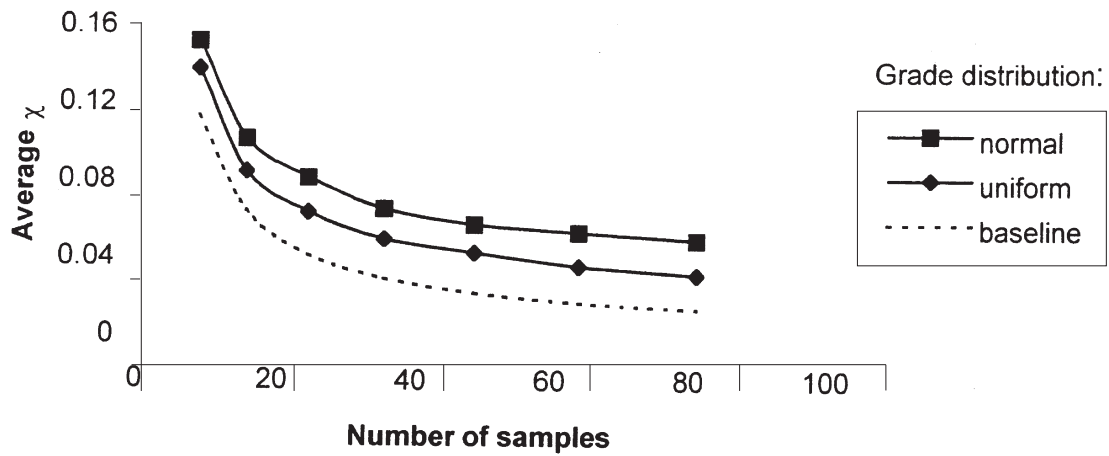

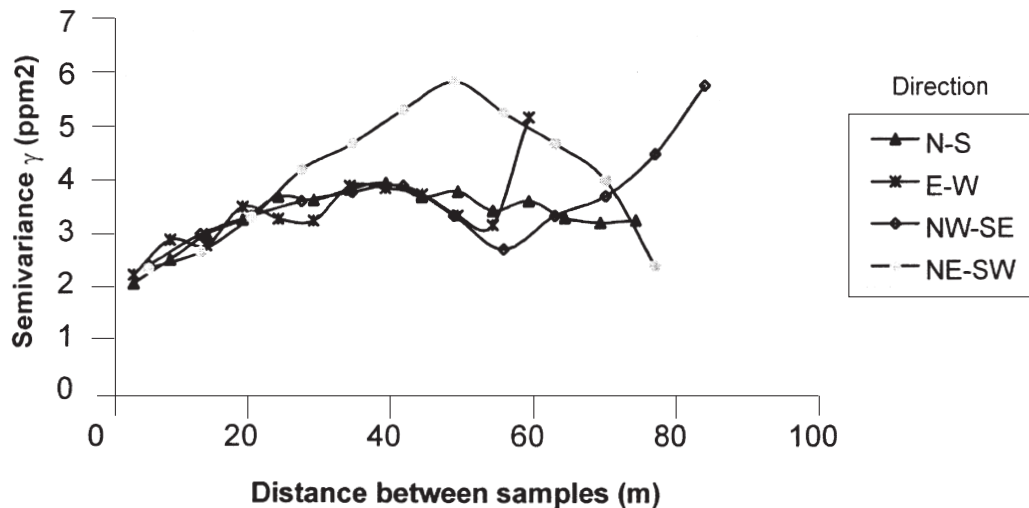**Figure 13—Effect of the distribution of grades for a regular grid**

Figure 14—Experimental semivariogram for a barite-gold deposit
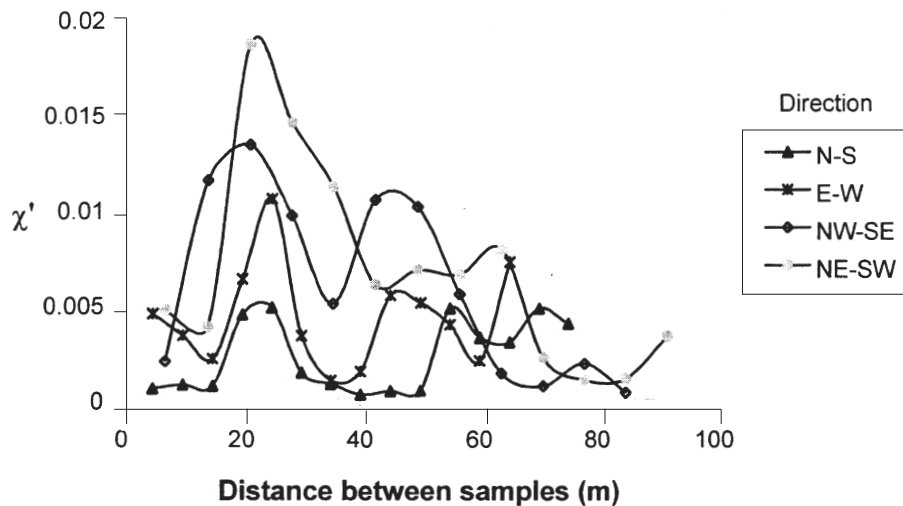
Method for assessing quality of the variogram

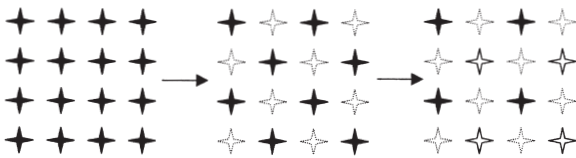**Figure 15—Development of χ' for a barite-gold deposit**

Figure 16. Principle of subdividing datapoints into 2 (middle) and 4 (right) subsets

Table I

Variation of $\bar{\chi}$ with the number of samples in a barite-gold deposit

Number of samples	240	120	60
Number of χ values	1	2	4
North–south	0.034	0.047	0.118
East–west	0.056	0.068	0.125
North-west–South-east	0.070	0.087	0.259
North-east–South-west	0.089	0.091	0.192

In practice, the distribution of the sampled locations is likely to be irregular, depending on a host of factors. This makes assessment of the average $\bar{\chi}$ or samples drawn at randomly selected locations of interest. Random distributions can display extreme clustering to fairly uniform distributions of sampled locations. Figure 12 shows that random distributions are initially worse than simulated clustered distributions (constant number of 3 clusters).

Up to now, grades sampled from a uniform distribution were used. To determine the effect of the grade distribution, simulations were performed with grades randomly sampled from a normal distribution with the same mean as previously used for the uniform distribution. The difference, shown in Figure 13, can be appreciated by scrutinizing the definition of $\bar{\chi}$. In the absence of correlation between the grades, the semivariance theoretically equals the unbiased variance. Substituting the semivariance in Equation [12] simplifies the definition of $\bar{\chi}$ to:

$$\bar{\chi} = \frac{1}{\sum_{l=1}^{T} m_l} \sum_{k=1}^{T} \left(\left| \frac{Cov\{x_i x_j\}_k}{Var\{x\}} \right| m_k \right) \qquad [13]$$

Hence, the upward shift in the curve relating to the normal distribution is explained by the combination of a reduced variance and a roughly constant covariance in the absence of correlation between the grades.

Application to real data

Interpretation of sample grades drawn from orebodies invariably differs from the analysis of randomly generated data. Spatial correlation between sample grades is likely to vary with the orientation of paired grades, making analysis in different directions necessary. Hence, values of $\bar{\chi}$ will be determined in the north–south, east–west, north-east–south-west, and north-west–south-east directions. Using sample data from Lerokis mine, pairs were classified in intervals defined by multiples of the closest distance between adjacent samples in a particular direction. This ensures that the density of sampled locations is similar in all directions. The semivariance versus the distance is plotted in Figure 14.

At face value, the semivariogram with the highest quality is observed in the north–south direction, followed by the north-east–South-west and east–west directions. The somewhat erratic trend at greater distances is mainly due to the sharp decrease in the number of pairs. This variation was taken into account by weighting the values for χ for each interval with the fraction of the total number of pairs. The development of the weighted value of χ, denoted χ', is shown in Figure 15.

In this case, summing the values of χ' to obtain the measure $\bar{\chi}$ confirms the visual assessment of the (semi)variogram: the highest-quality semivariogram is found in the north–south direction while the lowest-quality semivariogram is observed in the north-east–South-west direction. This correspondance suggests that 240 samples are sufficient for geostatistical interpolation, especially in the north-south direction ($\bar{\chi} = 0.034$). In order to determine the

effect of fewer samples, the datapoints were divided into two subsets containing 120 samples while maintaining a regular pattern in each subset. Each subset was subsequently split into two further subsets containing 60 samples each (Figure 16).

Values for $\bar{\chi}$ were determined for variograms based on each subset. Those relating to subsets of a similar size were averaged. Table I shows that $\bar{\chi}$ increases markedly during the transition from 120 to 60 samples. When no threshold for $\bar{\chi}$ specified, the minimum number of samples is located between 120 and 60.

Final remarks

Practitioners usually choose between the semivariance and the covariance when performing geostatistical calculations. Hence, the quality of a single curve is assessed by eyeballing the shape of the curve or the goodness-of-fit with one of the many expressions for the theoretical variogram. Deviations from the ideal shape are either explained as geological structures or ascribed to poor or insufficient data. Combining the development of the semivariance and the covariance provides additional insight into the variation in experimental variograms. Correctly accounting for the effect of bias, the proposed measure $\bar{\chi}$ is sensitive to all significant variables: the effects of the number of samples, the distributions of sampled locations, and the method for pairing datapoints are readily observed. The proposed measure $\bar{\chi}$ also presents a valuable tool when identifying the optimum number of samples which should be prepared and analysed in order to perform kriging with confidence. Further research is required to establish the effect of the distribution of sample grades and to set up a strategy for determination of a threshold value for $\bar{\chi}$.

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References

1. GLASS, H.J. and ZEGERS, T.W. Statistical aspects of sampling particulate matter. Proceedings: *Surface Mining*, Johannesburg, Glen, H.W. (ed.), The South African Institute of Mining and Metallurgy, 1996. pp. 157–164.
2. Davis, J.C. Statistics and Data Analysis in Geology, 2nd Edition, John Wiley & Sons, New York, 1986. ◆

Joint announcement by
Harmony Gold Mining Co. Ltd and Mintek*

Harmony and Mintek join forces to create Musuku Beneficiation Systems.

Johannesburg, 11 December 2002—Harmony Gold Mining Company Limited ('Harmony') (NYSE: HMY), the fifth-largest gold producer in the world, and Mintek, the leader in minerals and metals technology in South Africa, today announced that the parties had signed a Memorandum of Understanding to create Musuku Beneficiation Systems, an integrated manufacturing and technology group focusing on the beneficiation of precious metals.

Musuku, meaning gold in Venda, will introduce, through a combination of specialized refining technologies and standardized business management practices, a major paradigm shift in the way precious metals are processed by primary precious metals producers. It will provide the management, operational and technical services necessary to profitably integrate value-adding processes into the gold mining industry.

This approach will not only be applied to South Africa, but also to other countries where precious metals play a significant role in their economies, and where the use of their developed technologies can be deployed.

This is expected to unlock significant value in the value chain of the precious metals industry and help South Africa gain a dominant position in the downstream value-adding industries such as jewellery manufacture and industrial applications for precious metals.

In support of the recently announced Mining Charter, this new venture for the first time represents a significant opportunity for the participation of a Black Economic Empowerment company in the beneficiation of precious metals in South Africa. 'Through the Musuku initiative, it is anticipated that the operational expertise of the two companies, in the area of beneficiation of precious metals, will be leveraged to create a globally competitive value adding business,' said Paul Jordan, President and Chief Executive Officer of Mintek.

Harmony, the only producer to refine and market its own gold, recently upgraded its refinery in Virginia to produce in excess of 100 tons of refined gold per annum. A large range of value-added products are currently produced for the local and export markets. 'The creation of this business venture is the next logical step in extending the competitive advantage we have established over the past few years, to a larger market,' commented Ferdi Dippenaar, Harmony's Marketing Director. 'Our company has embarked on and supported a range of beneficiation projects which have resulted in benefits to all our stakeholders, i.e. our shareholders, the local communities in which we operate, and the local jewellery manufacturing companies. In addition these activities are creating employment opportunities in the Free State goldfields, an area which has a high level of poverty, and has an economy that needs to be regenerated following the downscaling of the mining activities in the region,' he concluded. ◆

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* *Issued by: Harmony Gold Mining Company Limited*
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A new look for Outokumpu technology*

'Our recent acquisitions, new structure and growing turnover make us more international, more competitive and better able to sustain long-term and close partnerships with our customers,' says Pekka Heikkonen, President of Outokumpu Technology, Espoo, Finland.

'To integrate the new companies† and strengthen customer services, we have restructured the organization into three Business Units and our international management team now consists of Neil Jagger from Australia as President of Mineral Processing BU, Peter Weber from Germany, President of Metal Processing BU, and Markku Jortikka, a Finn formerly working for us in Chile, as President of Services BU. Jean-Guy Coulombe, our new Canadian Vice-president for Marketing and Sales, will be based in Burlington, Canada,' he continues, 'with responsibility for strengthening customer services at our 16 sales companies. Our turnover in 2001 was E328 million; our target is E600 million by 2005 with increased profitability.'

High-tech CFB contract for Metal Processing BU

In September, Outokumpu Technology received a lump sum turnkey contract to design and build a circulating fluidized bed (CFB) pre-heater for the AUS\$ 43m (ca.E26m) first-of-its-kind, commercial-scale HIsmelt® plant at Kwinana, Western Australia. According to Peter Weber, 'HIsmelt is an exciting technology for maximizing the potential of lower grade iron ores. When combined with Outokumpu Technology's pre-heater expertise, it offers a low investment, low running cost source of pig-iron and constitutes a viable alternative to traditional blast furnace and coke-oven plants in both green- and brownfield situations.'

HIsmelt is a Rio Tinto process in which lower grade iron ore fines and ordinary steam coal are injected directly into a molten iron bath to produce high-quality pig iron. The consortium behind Kwinana comprises: HIsmelt Corporation P/L, Nucor Australia LLC, MC Iron and Steel P/L and China Shougang International Trade and Engineering Corporation.

Up to 70% capacity boost

Outokumpu Technology's CFB pre-heater is based on proven technology used in the 500,000 tpa, first-of-its-kind, Circored® direct-reduction plant commissioned in 1998 in Trinidad, West Indies. The Kwinana project will produce 800 000 tpa pig-iron suited to downstream processing. It is the potential forerunner of a much larger scale plant planned for the Pilbara region in NW of Western Australia.

The pre-heater for Kwinana, due for completion within 22 months, plays a particularly significant role in the HIsmelt process, because it dramatically increases productivity by pre-heating and pre-reducing the iron ore fines prior to injection into the Smelt Reduction Vessel (SRV). Because the process utilizes the hot off-gases from the direct smelting process, it saves energy and reduces overall emissions.

'To eliminate risk at this first-of-its-kind HIsmelt plant, the CFB-based pre-heater is designed for low pre-reduction degrees only,' comments Weber. 'However, even at this level, it will boost the output of the HIsmelt plant by 60%–70%. There is the possibility of using Outokumpu's Circofer® process, which is also a CFB-based pre-reduction process, for high levels of pre-reduction, which would allow to boost the output of the same HIsmelt Smelt Reduction Vessel by up to 300%.'

Closer partnerships

'A key difference between Outokumpu and other metal and mineral processing companies is that we have created and tested much of our technology in our own plants. This brings us closer to our customers and to understanding their needs,' explains Pekka Heikkonen. 'The strengthening of our sales companies across the globe will make these resources and capabilities more readily accessible in a bid to help our customers to add to their own businesses. As long-term partners, our resources range from technology, automation and financing to maintenance and even undertaking total operational responsibility for complete plants.'   ◆

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†*Lurgi Metallurgie, KDH Aluminium Technology, Eberhard Hoesch & Söhne, Royal Pannevis and Nordberg Mills*

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