PROFESSIONAL
DEVELOPMENT COURSES

Resource Estimation

SNOWDEN
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FOREWORD

This beautifully presented course manual supporting Snowden Mining Industry Consultants renowned course in Resource Estimation represents the culmination of more than 20 years of course refinements, revisions, improvements and further refinements. No doubt the manual will continue to be improved in the future as new information becomes available and new techniques are introduced. After all a course manual must be a dynamic, living document that remains relevant to the mining industry.

I presented my first short course in Geostatistical Resource Estimation at the University of Western Australia in 1986. Snowden Associates was established in 1987 as a consultancy providing geological and geostatistical resource estimation services and our very first employee, Christine Standing, was one of the course delegates of 1986.

Since the original manual was written to support what was later to become an internationally acclaimed course directly relevant to practicing mine and exploration geologists and mining engineers, several of Snowden's staff, expert in applied resource estimation and geostatistics, have played important roles in the course revision and updating process. Lynn Olssen is responsible for this particular revision of the manual and has substantially raised the bar with respect to its organisation and the quality of presentation.

This is a course for those who want to be (or have to be) practitioners in applied resource estimation. It is built upon real case studies and offers practical tips to assist those who have to get the job done. There is a strong emphasis on hands-on assignments.

The course and manual is designed to provide students, who have the appropriate background, with the tools that will allow them either to undertake serious resource estimation work or to be able to trouble-shoot or review resource estimates undertaken by others on projects that are inevitably subjected to intense scrutiny by investors.

Snowden's resource consultants and geostatisticians have for more than 20 years been leaders in the application of resource estimation techniques in the global mining industry. In many respects the company has set the standard. This manual encapsulates a distillation of Snowden's expertise.

Viv Snowden

17 May 2009

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1 Introduction

This manual provides a reference for geologists and engineers attending Snowden's Resource Estimation course. The purpose of this course is to skill geologists and mining engineers with tools and concepts for resource estimation.

The manual assumes the reader is from a mining environment, is attending Snowden's Resource Estimation course, and is working through the course activities and participating in the discussions. It is designed to follow the logical flow of a basic resource estimation process as would be carried out in real life. An introduction to some advanced concepts such as change of support and conditional simulation is included at the end.

The approach here has an emphasis on learning practical applications of geostatistics in the mining environment. Readers can discover more theoretical support to the concepts and discussions regarding geostatistical theory in Journel and Huijbreghts (1979) and Isaaks and Srivastava (1981). Additional reading material is referenced in Section 8.

Before tackling the resource estimation process it is important to understand what we are creating. So what is a resource estimate? There is often some confusion between the terms block model, resource estimate, resource model and Mineral Resource.

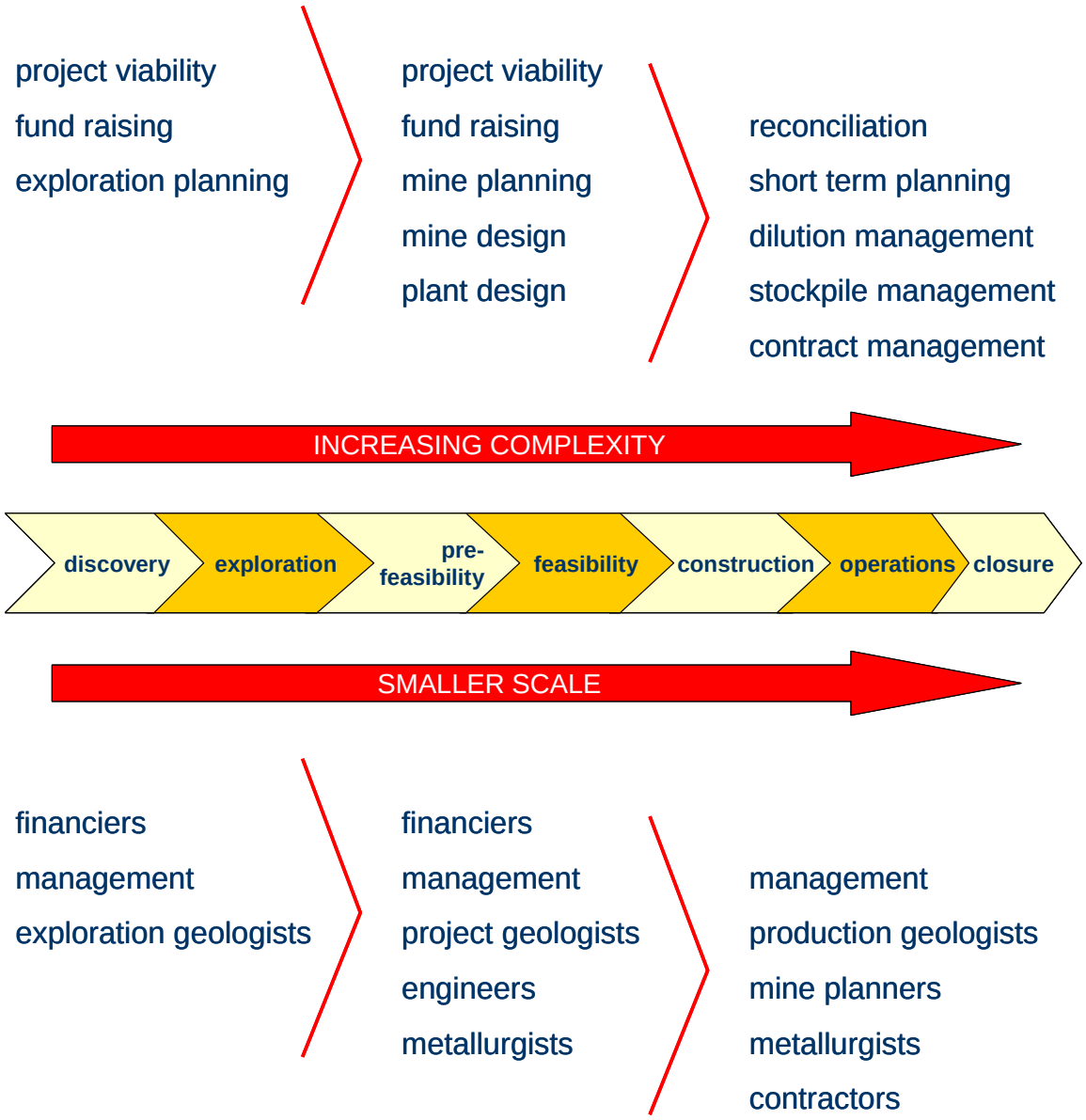
A block model is a three dimensional computer model representing small volumes or blocks with estimated grades for each of those volumes. Once it has been reviewed to ensure quality, assessed to determine the degree of confidence associated with each part of the process and documented it becomes a resource estimate. The terms resource estimate and resource model are interchangeable but must be consistently used. A block model and a resource estimate may include areas that are not reported as part of the final Mineral Resource.

A Mineral Resource is an estimate of the tonnes and average grade in a deposit. It is a set of figures not a model. The capital R in Resource means that it is reported to a recognised reporting code standard (JORC, SAMREC, CIM or equivalent). This means that it has reasonable prospects of economic extraction, has been reviewed to ensure quality, classified based on the degree of risk associated with the estimate and endorsed by a competent person.

Note that we talk about estimates rather than calculations because there are uncertainties at each stage in the process.

The resource estimate is an evolving entity which undergoes regular updates at each stage of the life of mine cycle. Over time it tends to increase in complexity and become focused at a smaller scale as more data and knowledge of the deposit is obtained. It is important that the resource estimate is a reliable reflection of the in situ Mineral Resource as it controls the financial expectations which form the basis of decision making at each stage of the life of mine cycle (Figure 1.1).

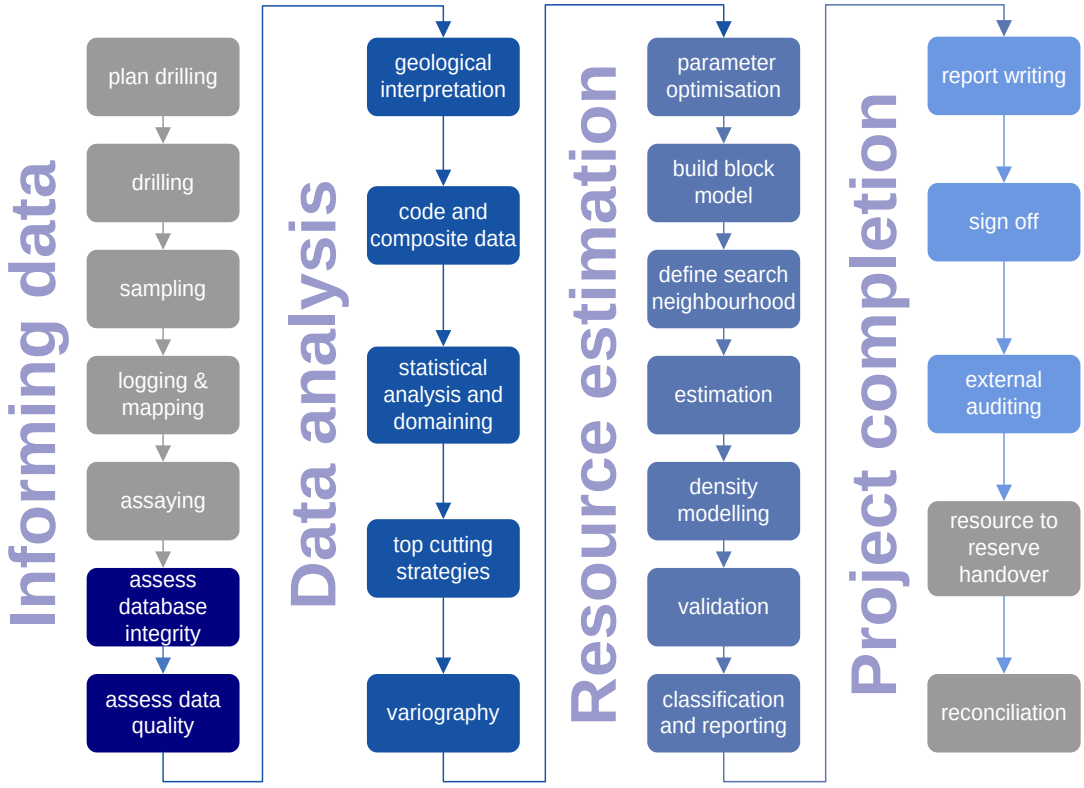
Figure 1.1 The life-of-mine cycle



1.1 Resource estimation overview

Figure 1.2 illustrates the basic flow for the resource estimation process and this manual is structured around these topics. An important note is to always have a peer review process in place throughout your project; each step should be reviewed to check for unintentional errors and the appropriateness of your methods.

Figure 1.2 Flow chart showing basic resource estimation process



1.2 Documentation

Good quality documentation is a critical component of the resource estimation process. Even if a full technical report is not required as the end product of a project, it is recommended that one is written to accompany a resource estimate. This report will be required for audits, peer review, future updates of the resource estimate and general referencing.

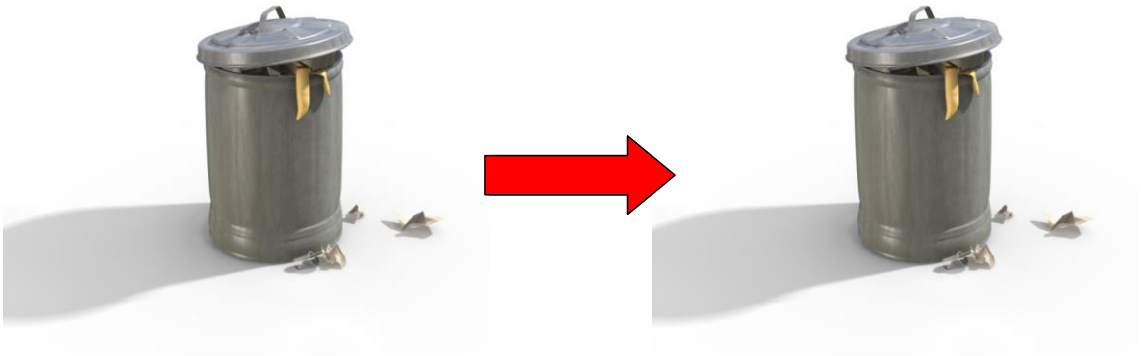
To facilitate the report writing, the resource estimation process should be documented on an ongoing basis throughout the project. It is recommended that report quality graphics be created during the process rather than at the end as this will limit the potential for rework being required.

Section 7.1 contains a list of recommended items for documentation at each stage of the resource estimation process.

2 Informing data

2.1 Database integrity

The database is a key asset of a company. Companies spend millions of dollars collecting data and if it isn't maintained properly then it's wasted. Database integrity is essential to achieving confidence in a resource estimate. If the database is incorrect then the resource estimate will be incorrect.



rubbish in rubbish out

The main question is whether the database is an accurate reflection of the data that has been collected. The following sections look at how to ensure an accurate database together with some pointers on data validation and associated data issues which can impact the resource estimate.

2.1.1 Data handling

Database

It is recommended that an industry standard database is used to store data; not a mining software package or a spreadsheet. All data transfers should be in digital format including geological logging. Manual or double entry of data should be avoided.

Systematic naming conventions should be used for database updates. It is important that everyone knows which database is the latest version and that all data corrections have been incorporated.

Ownership and management

Ownership and management of the database are paramount and data should be validated by the database administrator prior to updating the main database.

Backups and audits

It is important to have backups of the database including an offsite copy. Hard copies and/or original digital input files should also be retained and filed to allow for auditing. It is recommended that a random audit of 5 to 10% of the database is undertaken by cross checking the original data against the database.

Audit trail

Databases should have an audit trail to track what changes have been made. All validation issues and required changes should go through the database administrator for adjustment.

Data types

Databases are used to store several different data types which need to be understood:

- Raw data – unprocessed input data including assays, surveys, density, geological logging.
- Metadata – processed or calculated input data, for example, recovered grades or metal equivalents.
- Ratios.
- Averages of repeat assays.
- Validation and lookup tables.

An important note on averages: averaged data is often included in a database however it should not be used for resource estimation as this process can change the basic population statistics. The original value should be used unless the repeat or duplicate assays indicate that it is incorrect. Repeat and duplicate assays are designed to check the data quality.

2.1.2 Extraction and cut-off dates

Data for resource estimation should be extracted based on a cut-off date and the resource estimate can then be stated to be current as of that date. If an update is required, a full extract should be carried out again to prevent errors. The best policy is to set a cut-off date, not accept any new data after this and document the cut-off date.

2.1.3 Data validation

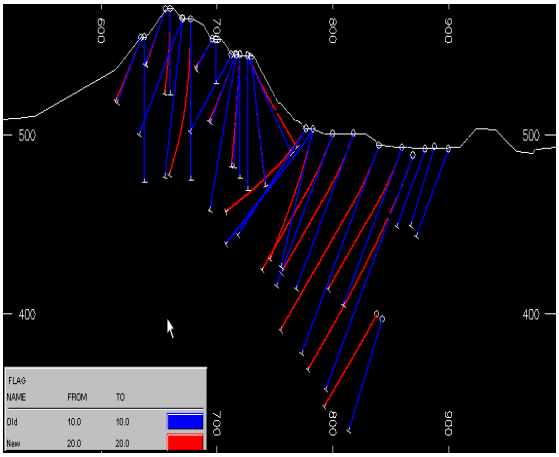
The standard drillhole data required for resource estimation are contained in the collar, survey, assay and geology tables. The collar and survey tables comprise point data and the assay and geology tables represent interval data.

Checks should be carried out on both the raw database tables and the final desurveyed data as some issues will only become apparent when viewed in three-dimensional space.

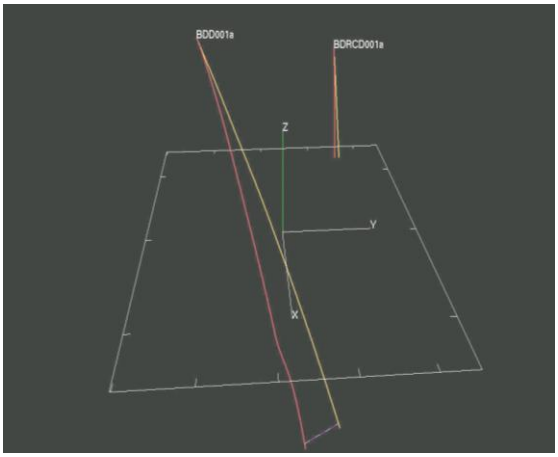
Appendix 7.2 contains a check list for validating drillhole data. All validation issues should be reported back to the database administrator for correction in the database. Figure 2.1 to Figure 2.4 illustrate some examples of common data validation issues such as:

- Duplicate records.
- Overlapping intervals.
- Collar elevation errors (compared to topography).
- Survey accuracy issues, for example collar survey versus downhole survey.

Figure 2.1 Examples of data validation issues – survey technique

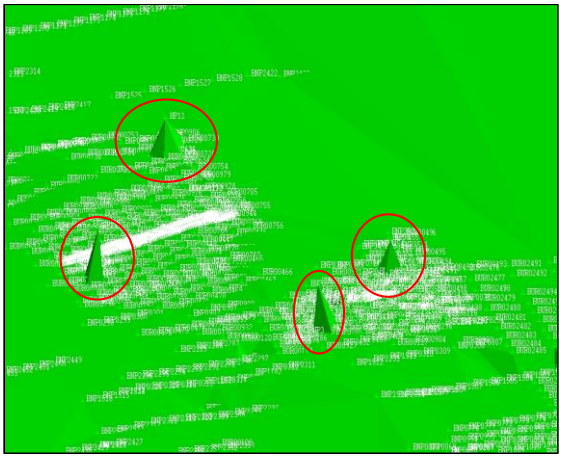


collar survey only versus downhole survey

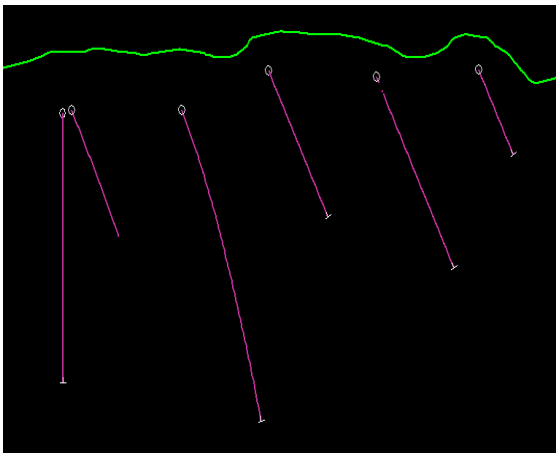


downhole survey technique (Eastman versus Gyro)

Figure 2.2 Examples of data validation issues – survey data

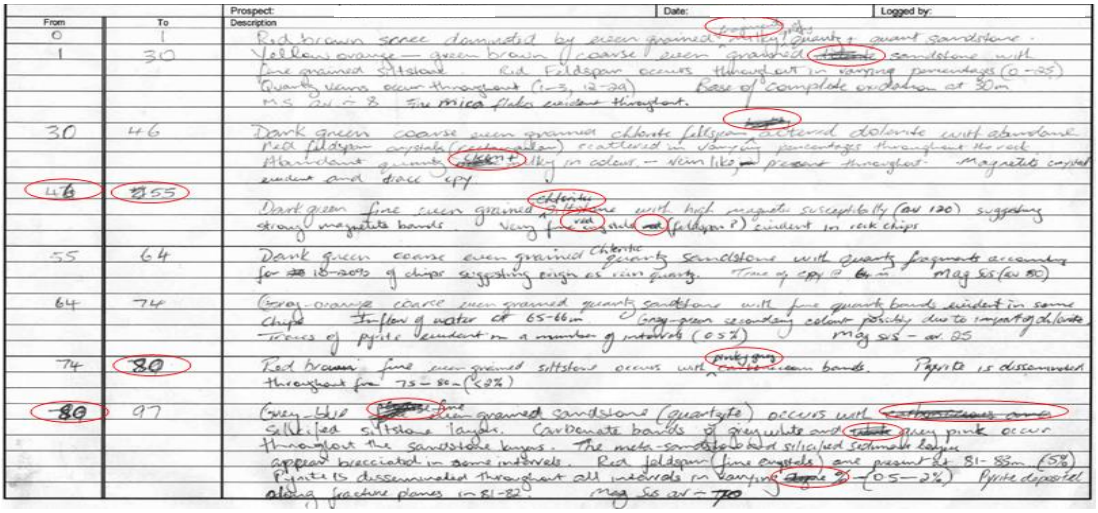


incorrect collar elevations used for topographic wireframe



collar elevations don't match topography

Figure 2.3 Examples of data validation issues – geological logging



unreadable and/or adjusted paper logs

Figure 2.4 Examples of data validation issues – interval data

BHID	SAMPNO	FROM	TO
DORC044	DORC445862	58	62
DORC044	DORC446061	60	61
DORC044	DORC446162	61	62
DORC044	DORC446263	62	63
DORC044	DORC446266	62	66
DORC044	DORC446364	63	64
DORC044	DORC446465	64	65
DORC044	DORC446566	65	66

overlapping from and to values

2.2 Data quality

Once confidence in the database has been established, the next step is to determine if the samples are representative of the mineralisation and if the assay results are accurate.

2.2.1 Sampling errors

Sampling is the act of collecting a small volume (the sample) from a larger volume of material (the lot) (Figure 2.5). In most instances there is only one opportunity to collect a good sample. The cost of sampling can be significant and money can be wasted with poor sampling.

Figure 2.5 Sampling from a lot

The main aim of a good sampling procedure is to ensure that the sample is representative of the lot. The reality of sampling is that the character of a sample can never be exactly the same as that of a large lot due to a variety of sampling errors.

Errors that occur during sampling are primarily due to the presence of heterogeneity in the lot. Heterogeneity is defined as the absence of homogeneity (where components are all strictly identical) and is the natural case as even apparently “pure materials” have some degree of “contamination” by other components.

Sampling errors can be separated into correct and incorrect errors.

Correct sampling errors occur due to the inability to obtain a representative sample due to the composition of the lot. Correct sampling errors cannot be removed, even when sampling is carried out correctly. Correct sampling errors include:

- Fundamental Sampling Error (FSE) – a function of the constitutional heterogeneity of the components making up the lot. This refers to the different components or minerals comprising the lot.
- Grouping and Segregation Error (GSE) – due to the distributional heterogeneity of the lot or the way the components are distributed. This refers to the way the different components or minerals are combined, for example one mineral may be preferentially associated with another.
- Point Selection Error (PSE) – due to heterogeneity within a flowing sample stream (for example a conveyor belt).

Incorrect sampling errors result from the design and implementation of the physical sampling and sub-sampling processes. These incorrect errors can theoretically be removed, although some are difficult to remove in practice. The three main incorrect sampling errors are:

- Incorrect Delimitation Error (IDE) – a result of a poor sample design process, resulting in a sample which is not representative of the lot (for example, the sample does not fully account for segregation).
- Incorrect Extraction Error (IEE) – due to incorrect extraction of the sample, resulting in a portion of sample being left behind or additional sample being taken.
- Incorrect Preparation Error (IPE) – results from changes to the sample after extraction. This can include:
  - Contamination where foreign material is added to the sample from elsewhere in the sample collection or preparation stream.
  - Loss of a portion of the sample after collection.
  - Alteration of the characteristics of the sample prior to analysis, such as oxidation of sulphides or loss of water in mineral lattice due to excessive heat.
  - Involuntary faults or operator error such as putting the sample in the wrong sample bag.
  - Deliberate faults such as fraud.

Figure 2.6 and Figure 2.7 illustrate the main incorrect sampling errors using an example of sampling from a partially segregated lot.

Sampling error is introduced at each sampling, sub-sampling and analytical stage and is additive. The total sampling error is the sum of the errors incurred at each stage (Figure 2.8).

Figure 2.6 Incorrect sampling errors – delimitation and extraction errors

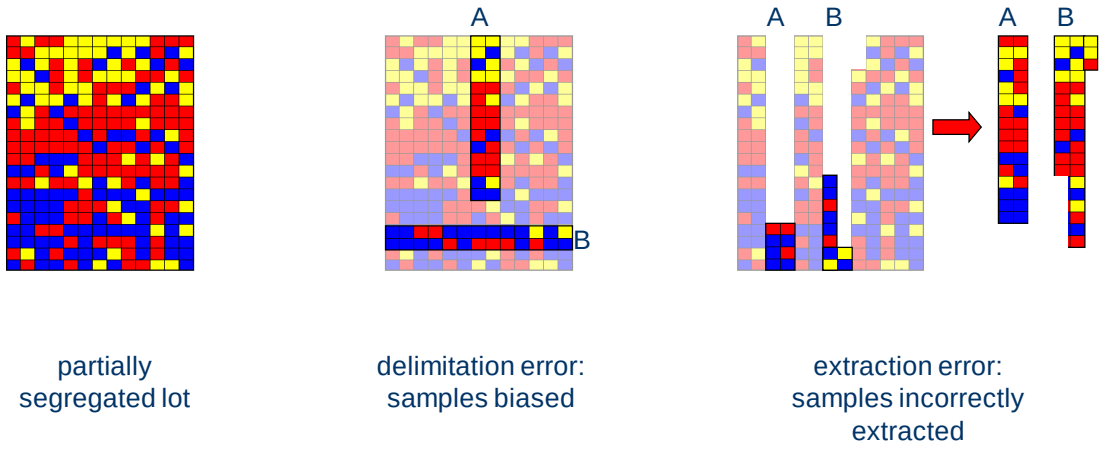


Figure 2.7 Incorrect sampling errors – preparation errors

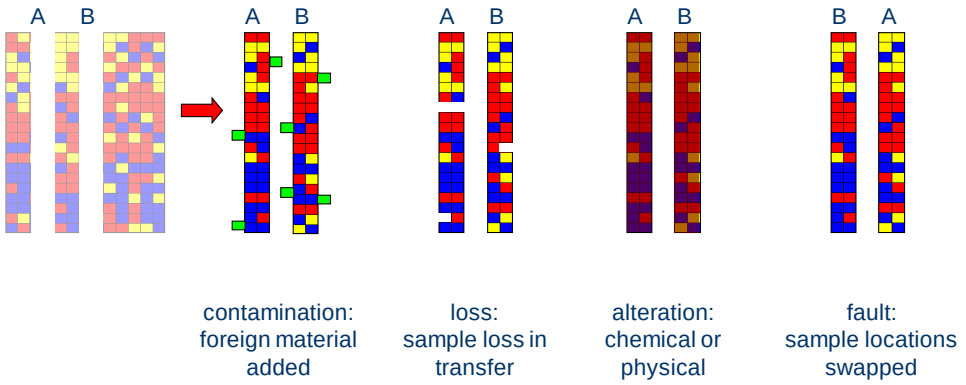
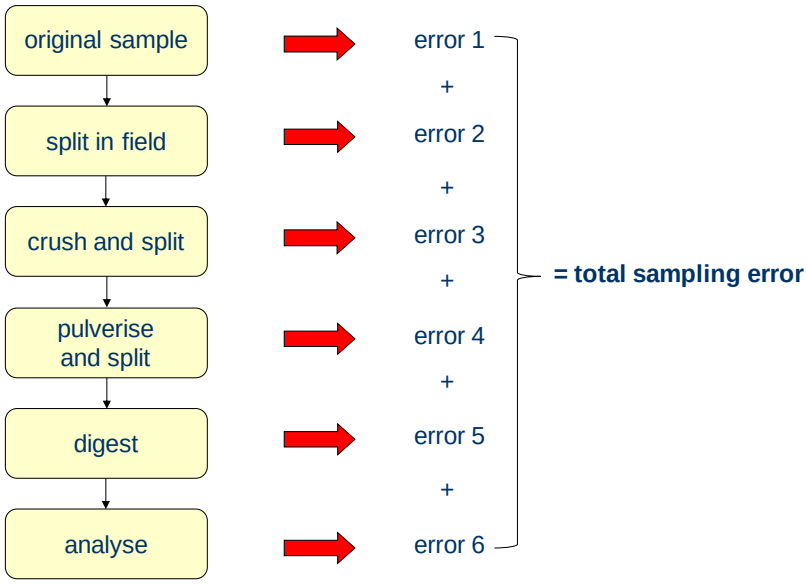


Figure 2.8 Total sampling error



2.2.2 Quality assurance and quality control systems

There are many stages that a sample must go through in order to obtain an assay result. It is important to have robust quality assurance and quality control (QAQC) systems in place to minimise errors at each stage, as well as procedures to be followed when errors are identified.

Quality assurance (QA) is the protocols and procedures which ensure that the sampling and assaying is completed to a certain quality. These systems should be designed to minimise sampling errors.

Quality control (QC) is the use of QAQC samples and statistical analysis to ensure that the assay results are reliable.

Terminology

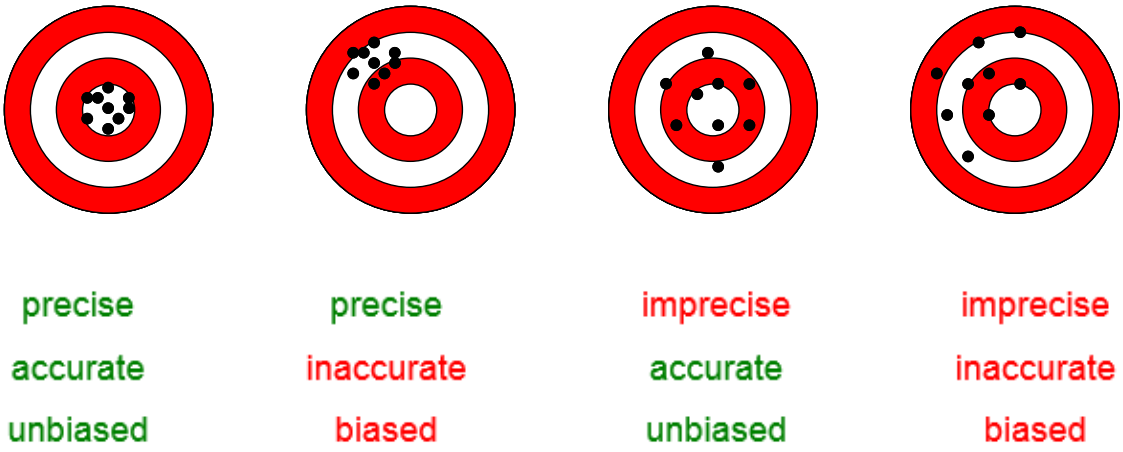
QAQC samples can be used to quantify the reliability of the assay results by determining their precision, accuracy and bias. These terms are defined as follows:

- **Precision** describes the spread or repeatability of results.
- **Accuracy** describes how close the average value is to the true value.

- **Bias** is the degree of difference between the average and the true value.

These concepts can be visualised as the scatter of pistol shots (or dart throws) on a target (Figure 2.9). The spread of the shots on the target is an analogy for precision and the average distance of the shots from the bullseye is a measure of accuracy. Where the average is not on the bullseye a bias has occurred.

Figure 2.9 Precision, accuracy and bias

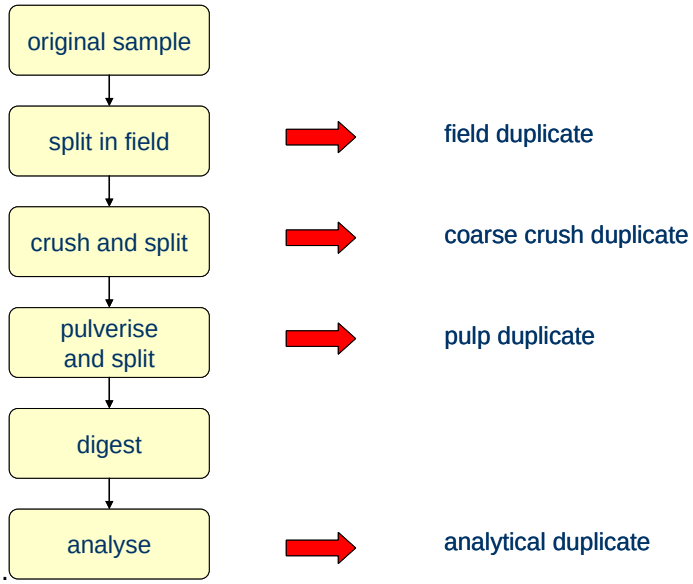


QAQC samples

It is important that QAQC sampling is representative of the deposit; i.e. equal levels of QAQC sampling should be carried across different mineralisation types, sample types and spatial locations. QAQC sampling includes:

- Duplicates:
  - Repeat samples usually generated by multiple splits of the same sample.
  - It is recommended that duplicates are taken at each size reduction and analysis stage of the process at a rate of 1:20 (Figure 2.10).
  - Common duplicates include field duplicates (second split taken during the original sampling), pulp duplicates (laboratory pulps resubmitted) and analytical duplicates (reanalysis).
  - Duplicates are used to assess precision or repeatability by comparing the paired (original and duplicate) data.
- Standards:
  - Reference samples with a known value and variability (standard deviation).
  - It is recommended that standards are submitted to the laboratory with the sample batches at a 1:20 ratio.
  - Standards are used to assess analytical accuracy and bias.
- Blanks:
  - Barren reference samples.
  - It is recommended that blanks are submitted to the laboratory with the sample batches at a 1:20 ratio and after mineralised zones.
  - Blanks are used to assess contamination during sample preparation.

Figure 2.10 Duplicate sampling in the sample preparation chain



Duplicate analyses

Precision is commonly assessed using the paired duplicate data by way of:

- Precision pairs plot which compares the half absolute difference (HAD) to the pair mean (Figure 2.11). The red reference lines indicate the relative HAD values (HARD). In this example, around 90% of the pairs have a HARD value of less than 5%.
- Ranked HARD plot which compares the half absolute relative difference to the pair mean (Figure 2.12). In this example the red lines highlight that 90% of the pairs have a HARD value of less than 5%.

Figure 2.11 Case study showing precision pairs plot for duplicate analyses

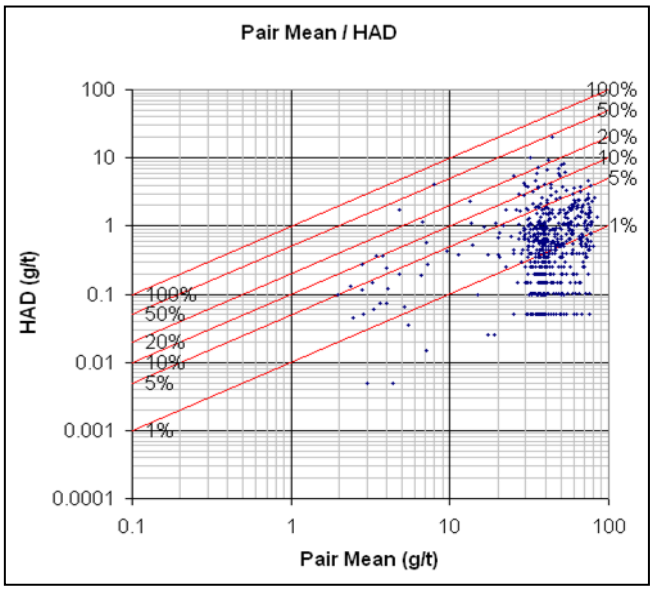
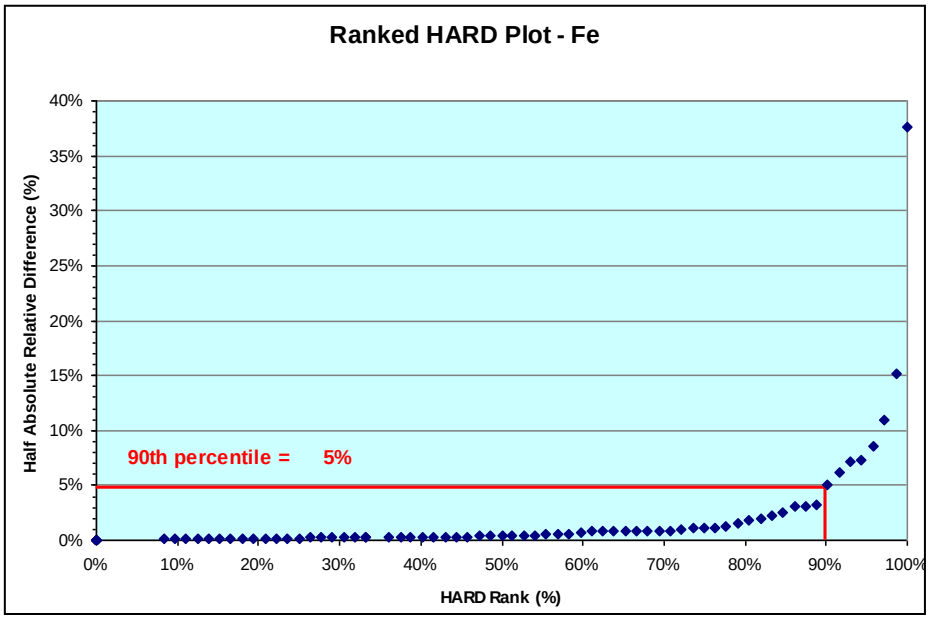


Figure 2.12 Case study showing ranked HARD plot for duplicate analyses



Sampling errors are cumulative and so the precision of field duplicates will be worse than the precision of pulp duplicates, as field duplicates are collected earlier in the sampling chain.

Precision will vary dependant on the attribute being sampled. As a rule of thumb:

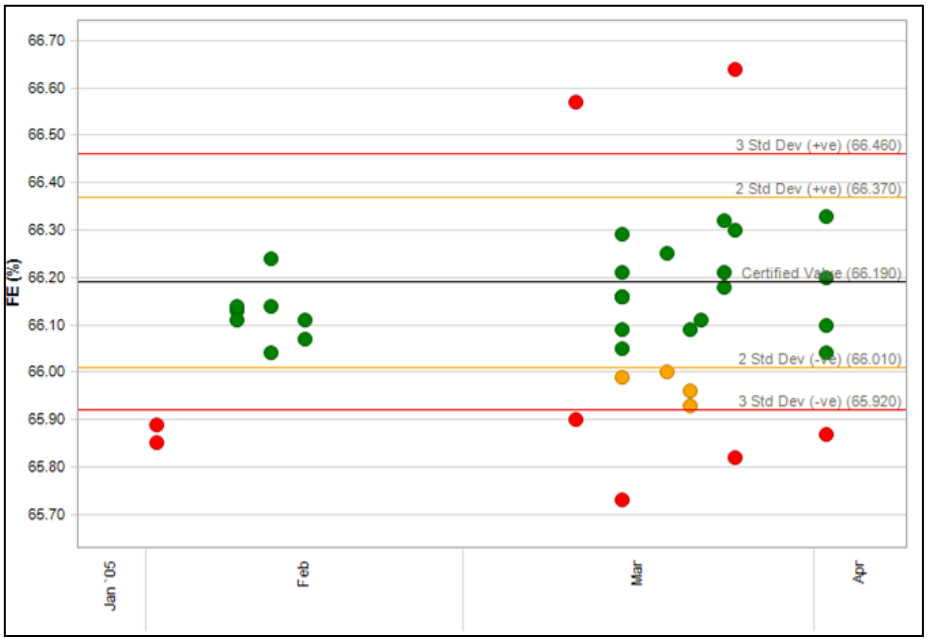
- Analytical duplicates can be expected to have 90% of the data within around 5% HARD for iron and 10% HARD for gold.
- Field duplicates may range from 10 to 20% HARD for iron and 20 to 30% HARD for gold.

Standard analyses

Standard samples are used to assess analytical accuracy by comparing the standard assay results to the expected grade of the standard. Bias can also be assessed by evaluating differences between the expected grade and the average of the standard results over time.

Standards are generally assessed using control charts which plot the results over time to highlight trends in the data. An example control chart for an iron ore standard is shown in Figure 2.13.

Figure 2.13 Case study showing standard control chart



The errors in assay results are usually normally distributed. This means that the expected standard deviation can be used to predict the probability of standard results falling within particular grade limits or thresholds, as follows:

- 68% of results should fall within ±1 standard deviation of the expected grade (7 in 10).
- 90% of results should fall within ±1.65 standard deviations of the expected grade (9 in 10).
- 95% of results should fall within ±2 standard deviations of the expected grade (19 in 20).
- 99.7% of results should fall within ±3 standard deviation of the expected grade (997 in 1000).

Typically a ±2 standard deviation limit is used as a warning limit. A ±3 standard deviation limit is used to indicate that a standard result is statistically out of control and may require a batch of samples to be re-assayed.

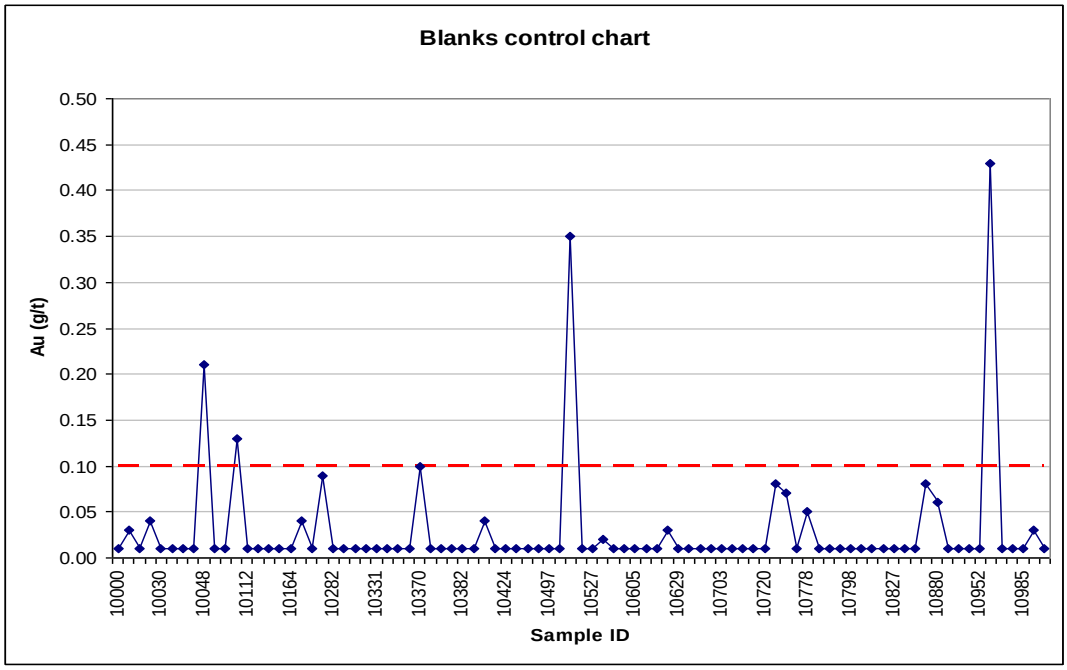
In Figure 2.13, each result is colour coded based on the number of standard deviations it differs from the expected mean; 8 out of 35 results fall outside of the ±3 standard deviation limit, indicating the potential for major laboratory issues.

Blank analyses

The primary use of blanks is to assess the cleanliness of the sample preparation within the laboratory. As the grade of a blank sample should be close to zero, any blank which reports a grade above a set threshold may be indicative of contamination during sample preparation.

The assessment of blanks is usually via a control chart, where the expected grade is the detection limit (Figure 2.14).

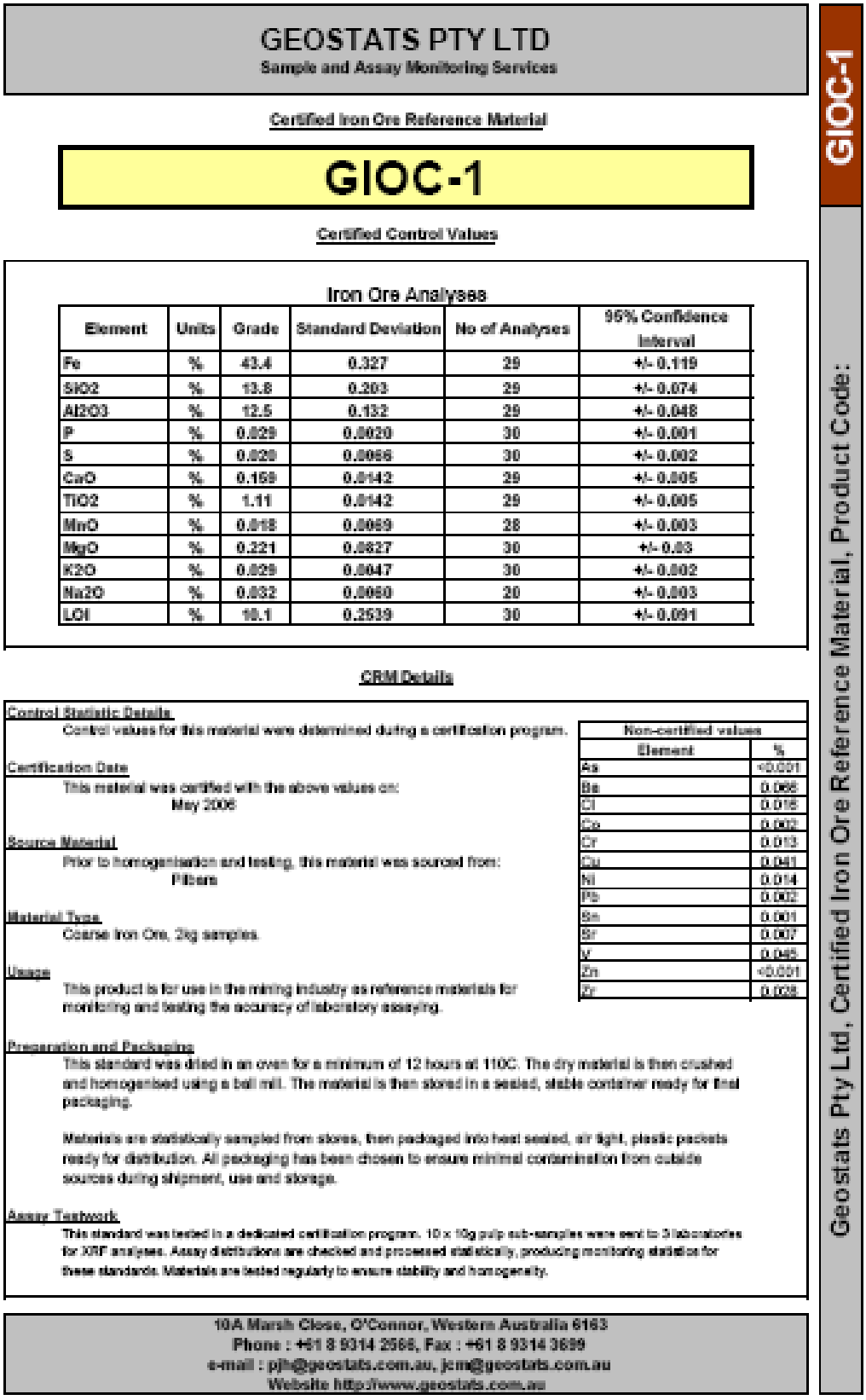
Figure 2.14 Case study showing blank control chart



Sourcing reference material

Certified reference material (CRM) can be purchased from companies such as Geostats Pty Ltd for a variety of commodities and material types. All certified reference material should come with a certificate detailing the expected grade and standard deviation. Figure 2.15 provides an example of a certificate for a coarse iron ore reference material from Geostats Pty Ltd.

Figure 2.15 Certificate for iron ore reference material



GEOSTATS PTY LTD
Sample and Assay Monitoring Services

Certified Iron Ore Reference Material

GIOC-1

Certified Control Values

Iron Ore Analyses

Element	Units	Grade	Standard Deviation	No of Analyses	95% Confidence Interval
Fe	%	43.4	0.327	29	+/- 0.119
SiO2	%	13.8	0.203	29	+/- 0.074
Al2O3	%	12.5	0.132	29	+/- 0.048
P	%	0.029	0.0020	30	+/- 0.001
S	%	0.020	0.0056	30	+/- 0.002
CaO	%	0.159	0.0142	29	+/- 0.005
TiO2	%	1.11	0.0142	29	+/- 0.005
MnO	%	0.018	0.0069	28	+/- 0.003
MgO	%	0.221	0.0827	30	+/- 0.03
K2O	%	0.029	0.0047	30	+/- 0.002
Na2O	%	0.032	0.0060	20	+/- 0.003
LOI	%	10.1	0.2539	30	+/- 0.091

CRM Details

Control Statistic Details
Control values for this material were determined during a certification program.

Certification Date
This material was certified with the above values on:
May 2006

Source Material
Prior to homogenisation and testing, this material was sourced from:
Pilbara

Material Type
Coarse Iron Ore, 2kg samples.

Usage
This product is for use in the mining industry as reference materials for monitoring and testing the accuracy of laboratory assaying.

Non-certified values	
Element	%
As	<0.001
Ba	0.066
Cl	0.016
Co	0.002
Cr	0.013
Cu	0.041
Ni	0.014
Pb	0.002
Sn	0.001
Sr	0.007
V	0.045
Zn	<0.001
Zr	0.028

Preparation and Packaging
This standard was dried in an oven for a minimum of 12 hours at 110C. The dry material is then crushed and homogenised using a ball mill. The material is then stored in a sealed, stable container ready for final packaging.

Materials are statistically sampled from stores, then packaged into heat sealed, air tight, plastic packets ready for distribution. All packaging has been chosen to ensure minimal contamination from outside sources during shipment, use and storage.

Assay Testwork
This standard was tested in a dedicated certification program. 10 x 10g pulp sub-samples were sent to 3 laboratories for XRF analyses. Assay distributions are checked and processed statistically, producing monitoring statistics for these standards. Materials are tested regularly to ensure stability and homogeneity.

10A Marsh Close, O'Connor, Western Australia 6163
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e-mail : pjh@geostats.com.au, jcm@geostats.com.au
Website http://www.geostats.com.au

GIOC-1

Geostats Pty Ltd, Certified Iron Ore Reference Material, Product Code:

3 Data analysis

Once the dataset is validated the next step is data analysis. Data analysis is carried out to describe the characteristics of the data and hence the population being estimated. The first step in analysing the data is to understand the geological controls on the mineralisation. This geological model is then used to create domains for estimation.

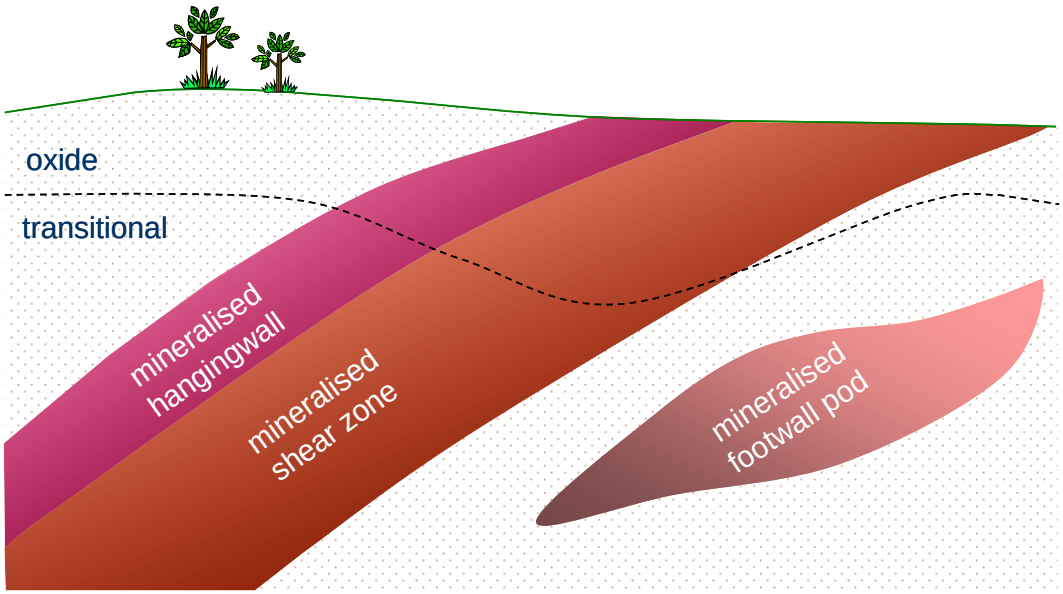
For resource estimation the underlying assumption is that the data being used is from a domain with stationarity. This means that the data is from a single statistical population and the mean and variance are consistent throughout the domain. Statistical analysis can be used to validate this assumption of stationarity.

3.1 Geological interpretation

A sound geological interpretation is the corner stone of a good resource estimate. The interpretation will influence the choice of estimation domains and methods.

The usual process for geological interpretation is to identify the dominant controls on mineralisation and to create wireframes to define each of these controls. Typical controls include structural, weathering and lithological controls (Figure 3.1). Grade boundaries are also common and will be discussed in more detail in section 3.1.3.

Figure 3.1 Geological interpretation



When defining controls the tendency is to focus on mineralisation but don't forget controls for things such as contaminants, density or other mining requirements.

Geological interpretations are usually carried out on a sectional basis and then connected to create three dimensional volumes or wireframes. The sectional interpretations need to be "snapped" to the drillholes for accurate compositing and sample coding and wireframes should be validated to check for holes or intersections which can cause errors during data coding.

3.1.1 Extrapolation

Standard practice with interpretations is to extend the interpretation for a distance of half the drillhole spacing from the data limits.

In addition the amount of extrapolation at depth needs to be considered. It is common to have some sections with deeper drilling than others. In this case the creation of a 'saw tooth' interpretation is not ideal if the deeper drillholes are indicating that the mineralisation is continuous. The recommendation is to treat these as areas of wider spaced drilling and push the interpretation through on sections where there is no data (Figure 3.2). These areas will have an increased level of risk which can be taken into account during the classification stage. The same situation can occur in plan view, where some drillhole lines are shorter than others (Figure 3.3).

Figure 3.2 Extrapolation at depth

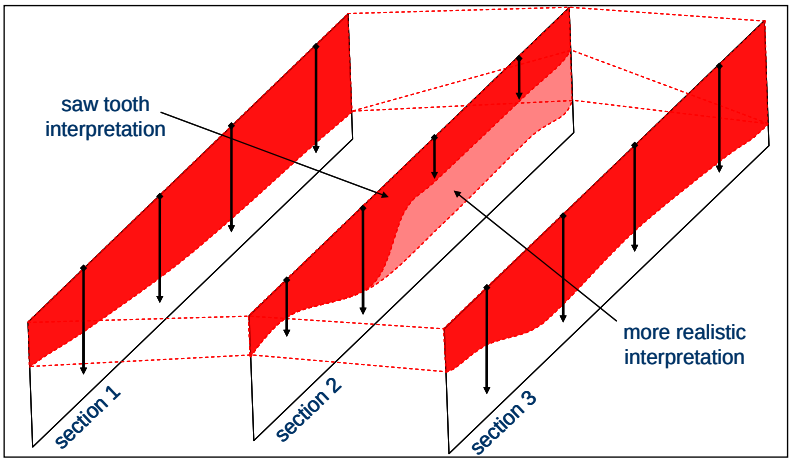
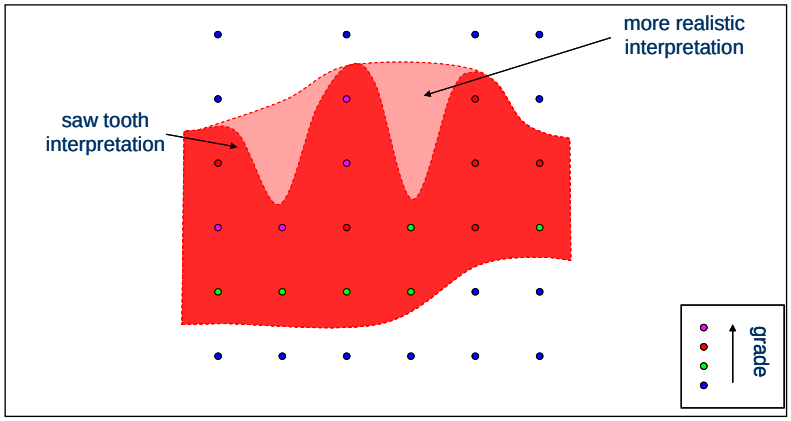


Figure 3.3 Extrapolation in plan view



3.1.2 Alternative interpretations

With any geological model there is a degree of uncertainty in the interpretation and often there may be more than one plausible interpretation. For example, is there potential for infill drilling to identify a more disjointed, poddy nature to the mineralisation than currently interpreted?

In order to quantify the risk in the interpretation it is recommended that any viable alternative interpretations be modelled and the tonnage change investigated.

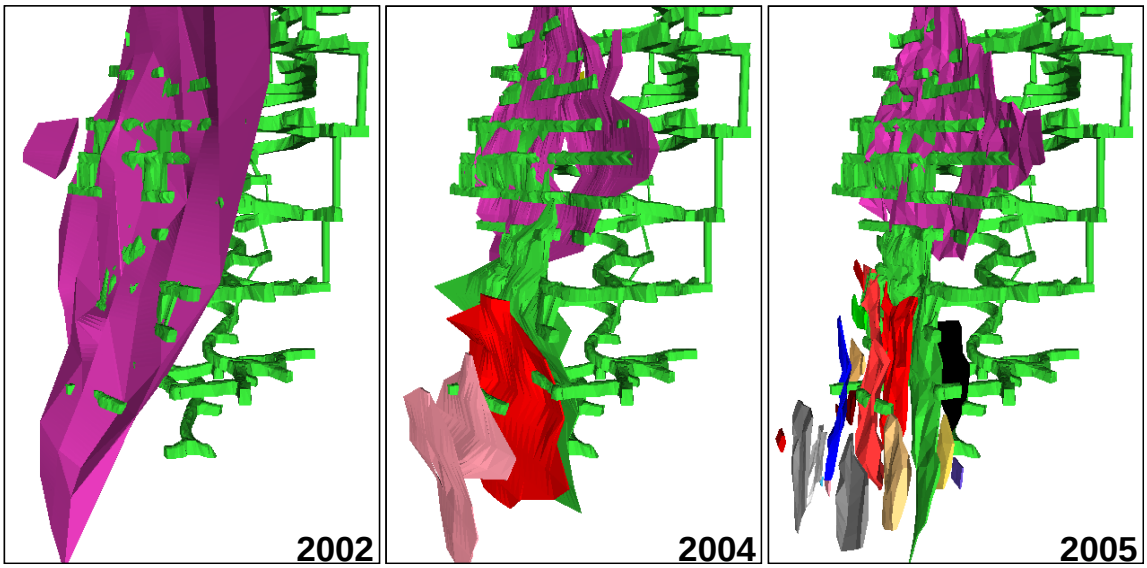
The following case studies highlight some of the potential issues related to interpretation.

Case study 1 – infill drilling in an underground scenario

Giant Reef's Chariot Gold Mine provides a classic example of the impact additional information can have on the geological interpretation. Three successive interpretations were carried out over a four year period, with additional drilling and production information available at each update (Figure 3.4).

The result was a major change from a single, continuous ore body to a poddy, discontinuous ore body. This change had the effect of reducing the resource by more than 30% metal and the reserve by more than 50% metal, ultimately resulting in an early mine closure.

Figure 3.4 Interpretation change with infill drilling



Case study 2 – shear versus lithology control on mineralisation

For this dataset two alternative geological interpretations were possible**:**

- Lithology controlled mineralisation.
- Shear zone control with mineralisation concentrated in en echelon gashes.

When the limestone is assumed to be main mineral bearing unit (Figure 3.5), the search ellipsoid is orientated parallel to lithology and a long search distance is applied. This results in grade smearing into and out of the shear zone. The economic impact is a shallow pit with a low strip ratio predicted for an overall low project value.

Conversely, when the shear zone boundary is recognised and used to domain the mineralisation, the search ellipsoid parallels the high grade en echelon tension gashes and a shorter search distance is applied (Figure 3.6). The economic consequence is a deeper pit with a higher strip ratio and, ultimately, a higher overall project value.

Figure 3.5 Lithology controlled interpretation

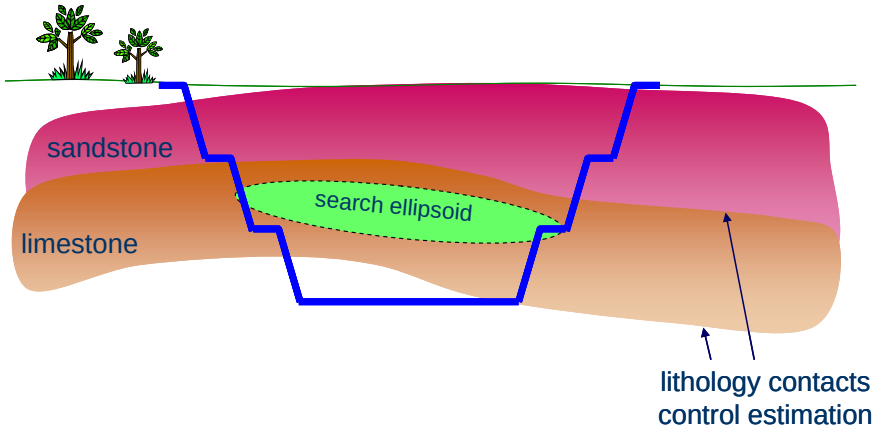
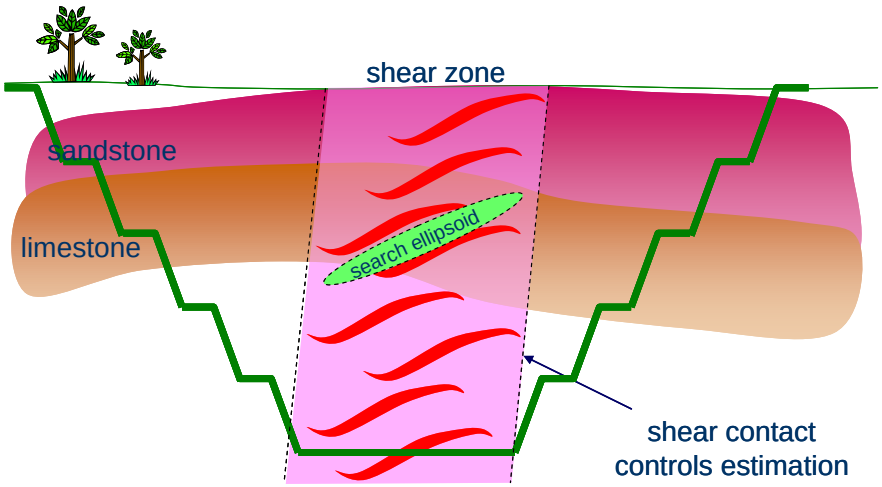


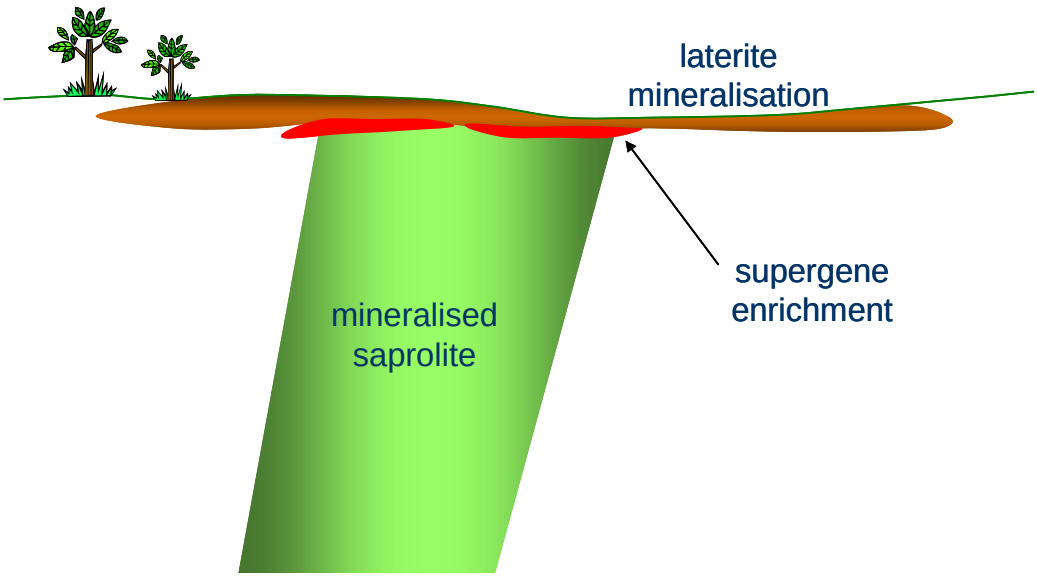
Figure 3.6 Shear controlled interpretation



Case study 3 - supergene in a laterite environment

For a lateritic environment with an enriched supergene zone, delineation and control of the grades within the enrichment zone is necessary to prevent grade smearing into the lateritic and saprolitic zones (Figure 3.7). Failure to do so will result in higher grades being predicted in the lateritic and saprolitic zones, thereby unrealistically raising the expectations of the ore body.

Figure 3.7 Supergene model



3.1.3 Grade cut-offs

The use of a nominal grade cut-off for defining areas of mineralisation is fairly common practice but should be approached with caution. If there is a geological or statistical reason for the grade change then using grade as a guide for domain definition is acceptable. The use of economic cut-offs for domain definition is not recommended.

3.2 Coding and compositing data

3.2.1 Coding data

The next step is to code the drillhole data using the validated wireframes. A standard set of codes should be developed for coding each of the domains.

Numeric rather than alphanumeric codes are recommended as this gives more flexibility in combining the codes for analysis and avoids problems due to transcription errors. For example if weathering codes are 1 and 2 these can be added to mineralisation codes of 10 and 20 to create combined codes for statistical analysis (11, 12, 21 and 22).

Some ways of checking that the data coding has been applied correctly include:

- The number of samples in the raw data should equal the total number of samples in the coded data.
- Visually check that the samples are correctly coded.
- Check the database for samples that may be missing codes.

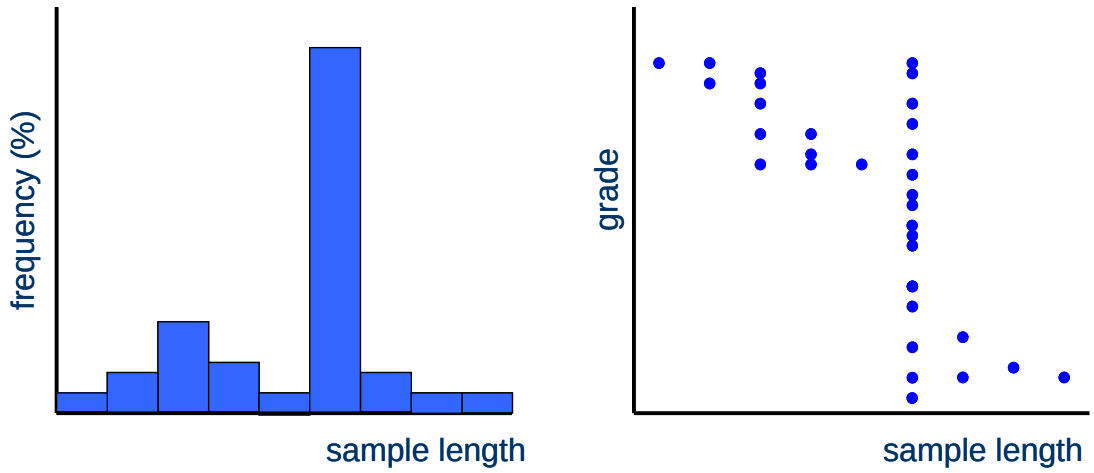
3.2.2 Compositing data

The objective of compositing data is to obtain an even representation of sample grades and to eliminate any bias due to sample length. There is no need to composite when all samples have the same sample length.

Compositing requires the selection of a representative composite length and the sample grades to be distributed along the drillholes with intervals that are equal to this length. When selecting an appropriate composite length:

- Look at the frequency of the sample lengths (Figure 3.8). Typically the dominant sample interval is selected as the composite length.
- Plot the sample grades against the sample lengths to see if there are any patterns (Figure 3.8). For example, are the lower grades generally associated with the longer sample lengths? What biases may have been introduced with the sampling protocols?
- Review any small sample lengths. Are they real? Lots of small sample lengths may mean that wireframes are not snapped to drillholes.
- Review any long sample lengths. Long samples may not be suitable for inclusion in the dataset. These are usually not sampled and so are not a significant issue.
- In compositing data the aim is to minimise the degree of sample splitting. Over splitting samples into smaller composite lengths can result in an over smoothed view of the short scale grade variability.
- Data can be composited to longer lengths than the sample interval. This will generally lower the variance and smooth the variography. However it will also reduce the amount of data available to work with.

Figure 3.8 Composite length selection



There are two main methods of compositing:

- Downhole compositing from the collar:
  - With no boundaries.
  - With breaks at boundaries.
- Bench compositing within anticipated vertical slices (for example bench heights).

Downhole compositing is recommended for resource estimation.

If the domain boundary is gradational, then downhole compositing with no domain constraints may be appropriate (Figure 3.9). If this method is selected then the data will need to be coded after compositing as domain codes can be lost or averaged across the boundaries. This method might also be used when the boundary position is uncertain.

If the domain boundary is abrupt, then it is more appropriate to composite within wireframe boundaries (Figure 3.10). This means that the composited sample intervals will be split at the boundary and there will be no smearing across the boundaries.

Methods for assessing the boundary conditions are discussed in 'Boundary analysis'.

Figure 3.9 Downhole compositing with no boundary constraints

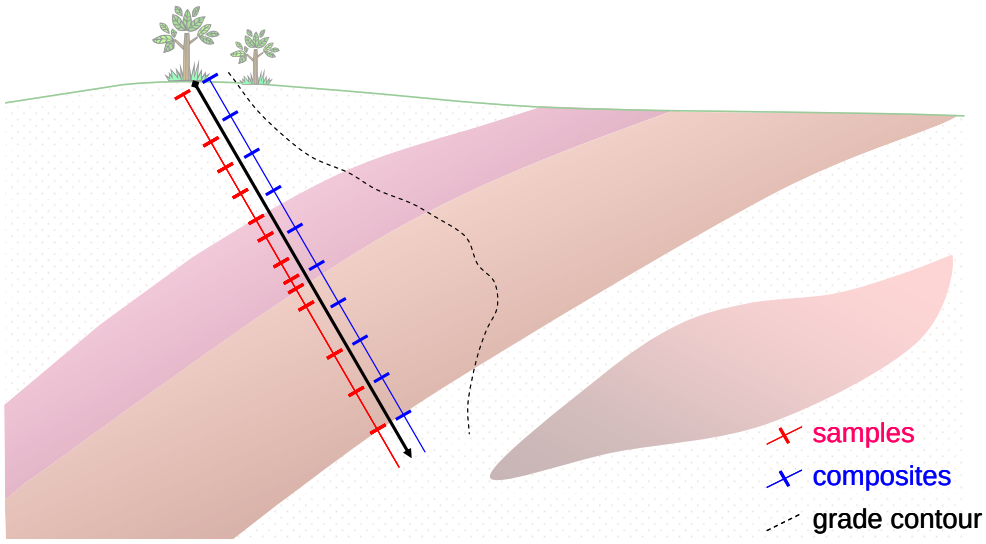
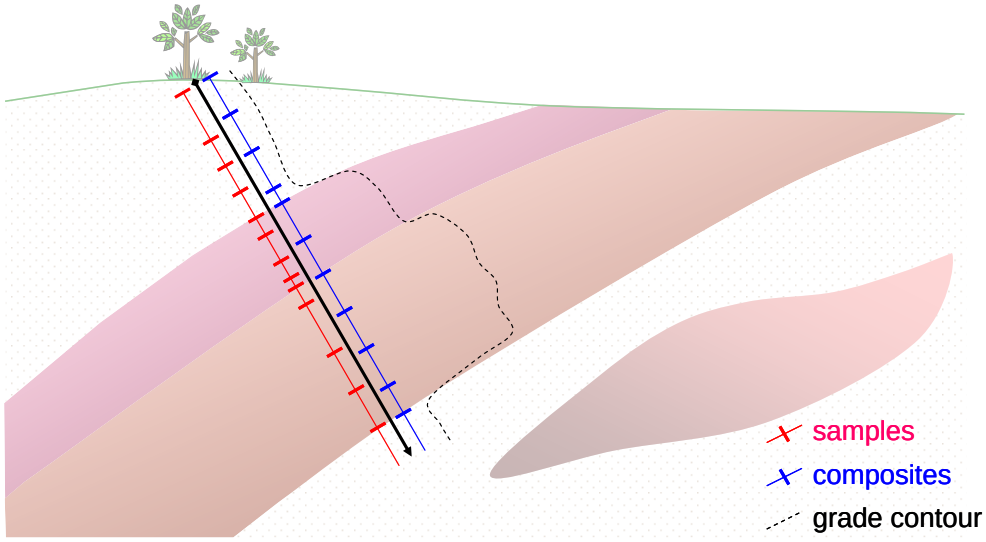
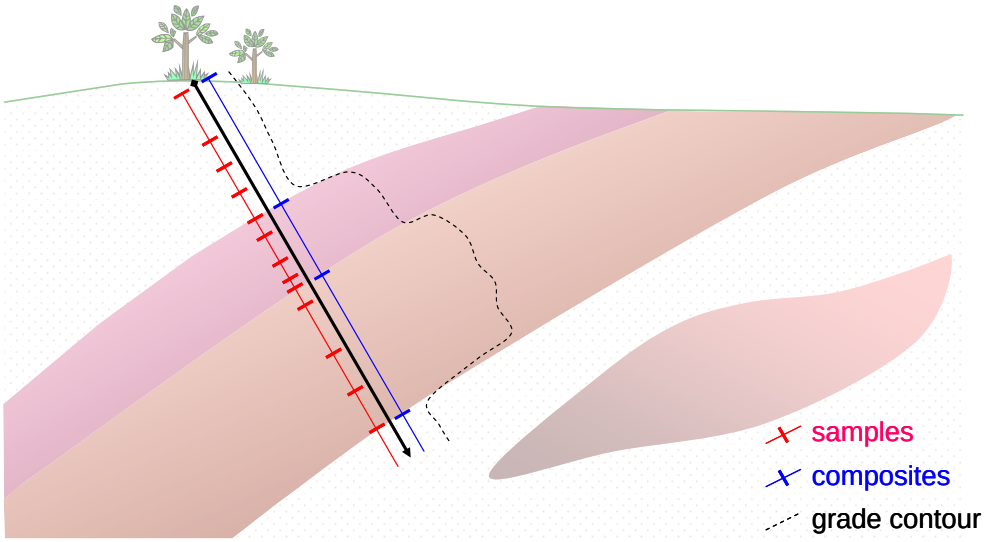


Figure 3.10 Downhole compositing with boundary constraints



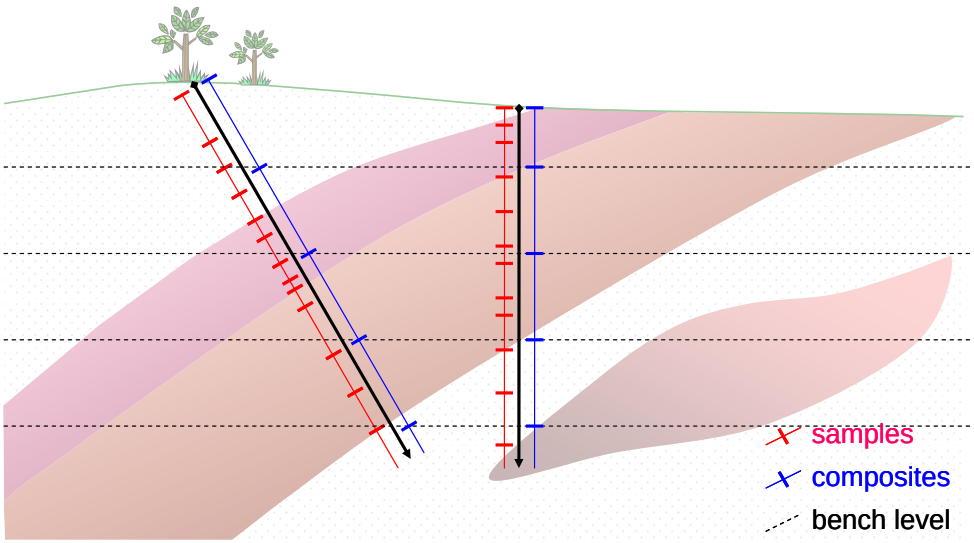
For narrow vein mineralisation styles where the length of the intercept is strongly correlated with grade it may be best to composite over the domain thickness. This method results in one composite per domain intercept, and the composites will have variable lengths (Figure 3.11).

Figure 3.11 Downhole compositing with boundary constraints – over a domain



If working in an environment with a definitive bench height and the drillholes all have similar orientations, there is the option to composite over the bench height. This method is sometimes used in grade control situations where there are vertical drillholes and the deposits are flat lying. This method is not normally recommended if the drillhole orientations vary as there will be unequal representation of the composite lengths and the potential for a bias (Figure 3.12).

Figure 3.12 Bench compositing

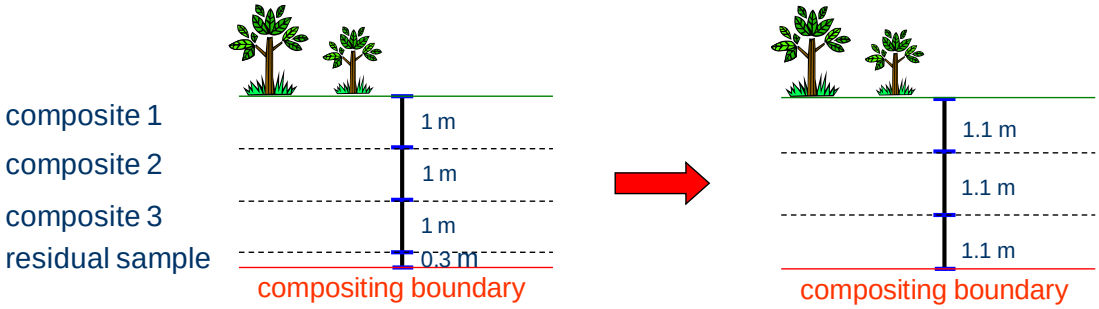


There are several other items to consider once you have selected your composite length and method. The options will vary dependant on software so you need to be aware of how your software deals with these. The main items are:

- Treatment of missing assays or gaps in the sampling.
- Treatment of residuals: residuals are the small lengths at the end of the drillhole or at a domain boundary where the sample length is less than the minimum composite length (Figure 3.13). Options for dealing with residuals include:

  - Setting a minimum composite length where any samples smaller than this length are discarded. If there are any grade trends within the domain whereby there is higher or lower grade near the boundaries, this method is not recommended as it can introduce a bias.
  - Rescaling the composites so that the interval is kept as close to the selected composite length as possible, while including the residual lengths (Figure 3.13). In practice this means that if the residual is less than half the selected composite length, the composite lengths will be increased. If the residual is greater than half the composite length, an additional composite will be added and the lengths will be less than the selected composite length.
- Density weighting for compositing: should only be used if there is a very strong correlation between grade and density.

Figure 3.13 Residuals



Some ways of validating the composite grades include:

- Visually check the composite grades against the sample grades.
- Look at a histogram of the raw and composited lengths to make sure they look as expected.
- Check the total composite length equals the total sample length (composites may be slightly less if discarding residuals).
- Check the mean of the composites equals the length weighted mean of the samples.
- Look at the minimum composite grade compared to the minimum sample grade.

3.3 Statistical analysis and estimation domaining

This section deals with the statistical concepts and tools used to describe grade populations.

Geostatistics is a branch of applied statistics for variables correlated either in space (for example drillhole samples) and or time (for example belt sampling). This is a major departure from classical statistical methods which treat individual samples as being random and independent.

Geostatistics is a set of tools developed by Professor Georges Matheron based initially on the work done by Krige, Sichel and de Wijs on the gold deposits of the Witwatersrand in the 1950's and 1960's. Matheron built the major concepts for the theory for estimating resources, which he called "Geostatistics", and published the underlying basis for these tools in 1970 in the "Theory of regionalised variables".

3.3.1 Describing statistical populations

Basic statistics

There are two main groups of statistics that we need to understand for geostatistics:

- The measures of central tendency:
  - What is a typical grade for this domain? Is it high grade or low grade? Is it economic?
- The measures of spread:
  - How different are the sample grades from the typical grade statistics? Is the domain consistently high grade or is there a lot of variability and uncertainty?

The statistics used to describe measures of central tendency are the mean, mode and median.

- The **mean** is the sum of all the sample values divided by the number of samples. The mean is the same as the average value.

$$mean = \frac{sum\ of\ sample\ values}{number\ of\ samples}$$

- The **median** is the middle value and is determined by sorting the data into ascending order and selecting the middle value. The median is the same as the 50^{th} percentile where half the data lies below this sample value and half the data lies above this sample value.

$$median = 50^{th}\ percentile$$

- The **mode** is the most frequently occurring sample value.

$$mode = highest\ frequency\ value$$

The statistics used to describe measures of spread are the range, inter-quartile range, variance, standard deviation and coefficient of variation.

- The simplest spread statistic is the **range**. The range is the difference between the highest and lowest sample value.

$$range = \text{maximum value} - \text{minimum value}$$

- The **inter-quartile range** tells us something about the range of the sample values which represent the middle 50% of the samples. It is calculated by sorting the data into ascending order and determining the sample which has 25% of the data below this value (25^{th} percentile) and the sample which has 75% of the data below this value (75^{th} percentile). The inter-quartile range is the difference between the 75^{th} and 25^{th} percentiles.

$$\text{inter-quartile range} = 75^{th} \text{ percentile} - 25^{th} \text{ percentile}$$

- The **variance** measures the typical difference between the actual sample values and the overall average value. The differences between individual sample values and the average values are each squared (to prevent positive and negative differences cancelling each other out). These squared differences are accumulated and divided by one less than the number of samples. A value of one is subtracted from the number of samples because the sample values are being compared to a statistic that is based on the sample values themselves rather than the population. Ignoring this would tend to underestimate the true variance, hence n-1 is used to account for the bias. This is called “losing a degree of freedom”.

$$variance = \frac{\text{sum of (sample value-mean)}^2}{\text{number of samples - 1}}$$

- The **standard deviation** is the square root of the variance.

$$\text{standard deviation} = \text{square root of variance}$$

The **coefficient of variation** (CV or COV) is used to compare the variability of datasets. It is often called the relative standard deviation as it is the ratio of the standard deviation to the mean value. The standard deviations of datasets can only be compared directly when the datasets have the same means. The coefficient of variation makes the standard deviation relative to the mean grade and hence the values can be directly compared.

$$CV = \frac{\text{Standard deviation}}{\text{mean}}$$

Population distribution is also an important aspect of statistical analysis. The distribution can be described in terms of the skewness sign which is an indication of the difference between the mean and the median (mean – median) (Figure 3.14).

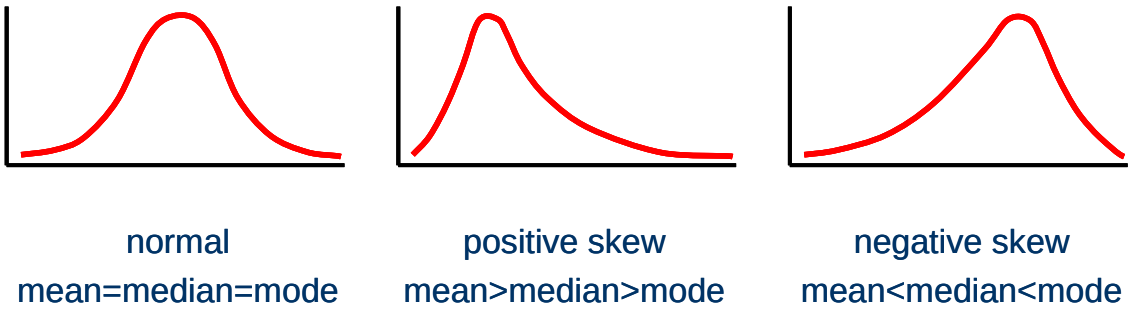
When the data distribution is plotted as a histogram (number of samples within a series of grade bins plotted against that grade), a distribution is not skewed if it shows a symmetrical, bell shaped curve. In this instance the mean, median and mode are approximately equal.

If the distribution tails to the right then the mode is less than the median, which is less than the mean and the distribution is positively skewed. Examples of positively skewed data include gold, copper, sulphide nickel, platinum and many contaminants in iron ore.

If the distribution tails to the left then the mode is greater than the median, which is greater than the mean and the distribution is negatively skewed. An example of negatively skewed data includes iron in iron ore deposits.

Raw mean and variance are sensitive to extreme values and hence as the level of skewness increases it becomes harder to produce reasonable estimates that reflect the population characteristics.

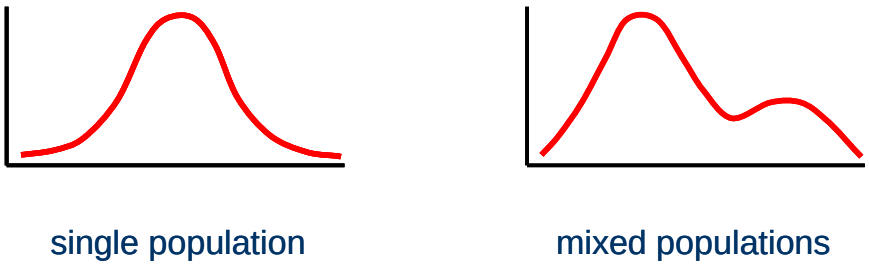
Figure 3.14 Population distribution



The population distribution can also be used to determine the presence of two or more statistical populations. Single statistical populations will show a smooth curve with a single peak on the histogram while mixed populations will show up as multiple peaks (Figure 3.15).

Many estimation methods are parametric in that they assume a single statistical population.

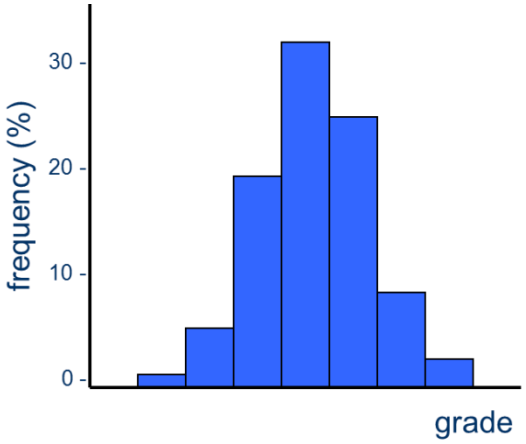
Figure 3.15 Single and mixed population shapes



Histograms, cumulative distribution functions and probability plots

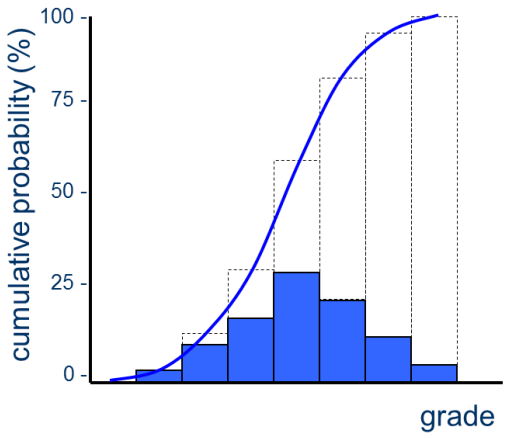
There are three main graphs that are used for statistical analysis. Histograms, cumulative distribution functions and probability plots. Histograms provide a graphical summary of the number of samples that have grade within a range of intervals (Figure 3.16). For non-skew, normally distributed data the histogram should show a normal, bell-shaped curve.

Figure 3.16 Histogram



A cumulative distribution function (CDF) is an accumulated histogram where the proportion of samples below each grade threshold (cumulative probability) is plotted against that grade (Figure 3.17). CDF's can be generated by sorting the data in ascending order, calculating the percentile values for each sample and plotting the percentiles against the sample grades. The percentile is simply the relative position of the grade, for example the 10th percentile has 10% of the samples being lower grade and 90% being higher grade. CDF's are "S" shaped when the data is not skewed. CDF's for negatively skewed data are steep at the high grade end while CDF's for positively skewed data are steep at the low grade end.

Figure 3.17 Cumulative distribution function



Probability plots are a variation on the CDF where the probability scale is adjusted so that the graph forms a straight 1:1 line if the population is normally distributed. The graph effectively maps the data distribution against a standard normal (bell-shaped) distribution (Figure 3.18).

Figure 3.18 Probability plot

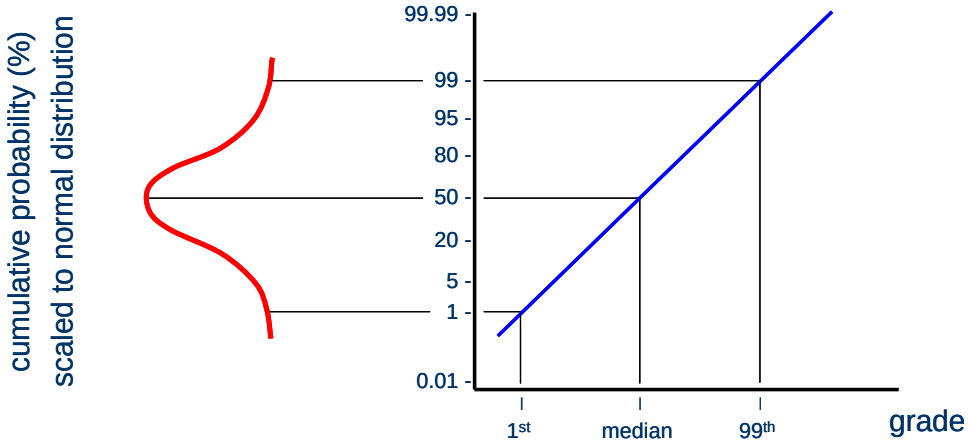


Figure 3.19 to Figure 3.21 illustrate histograms, CDF's and probability plots for normal, negatively skewed and positively skewed distributions respectively.

Figure 3.19 Graphs for normal population

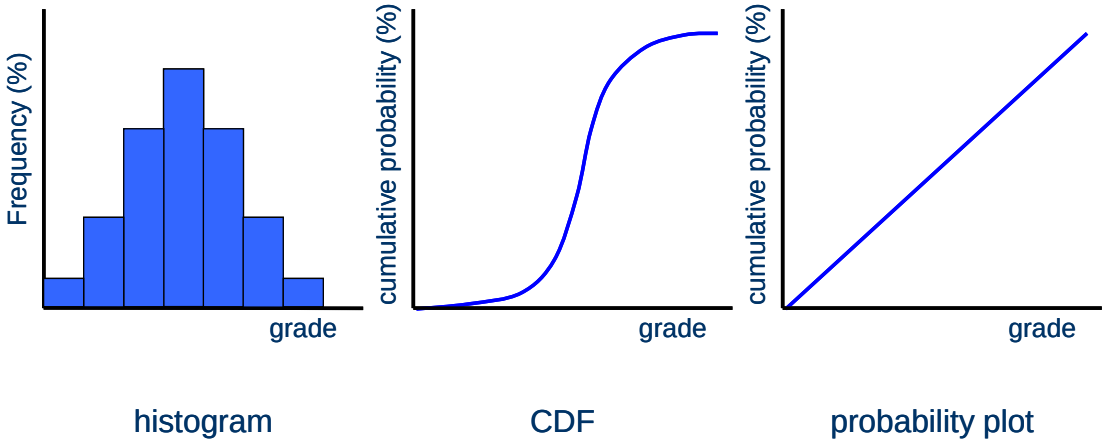


Figure 3.20 Graphs for negatively skewed population

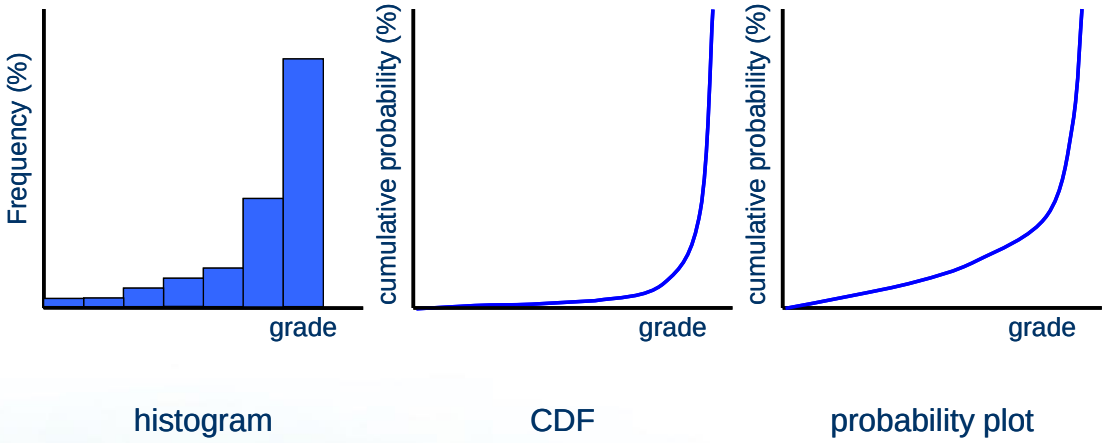
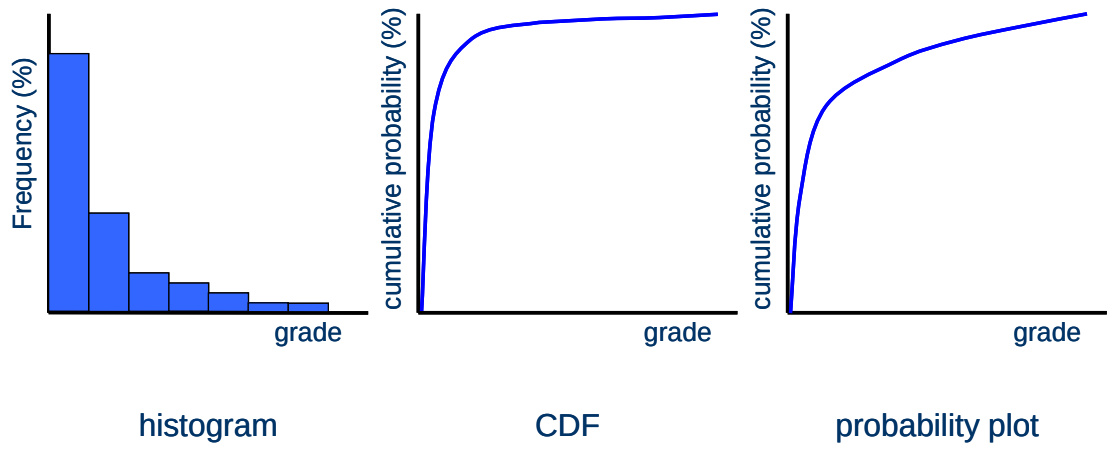


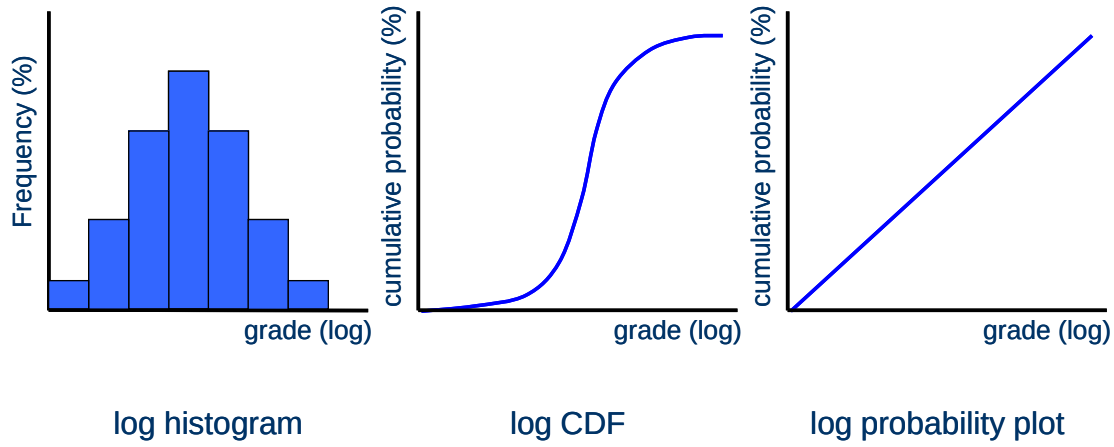
Figure 3.21 Graphs for positively skewed population



For positively skewed data, plotting these graphs in log scale can provide a better view of the population. The log scale has the effect of compressing the range of high grades and expanding the range of low grades.

Transforming a positively skewed histogram to log scale gives a normal, bell-shaped curve if the population is log normally distributed. Similarly, transforming a CDF to log scale gives an S shaped curve if the population is log normally distributed and transforming a probability plot to log scale (log probability plot) gives a straight 1:1 line if the population is log normally distributed (Figure 3.22).

Figure 3.22 Log scale graphs for positively skewed population



CDF's and probability plots are useful for reading off probabilities of grade above or below any given cut-off grade and are used in indicator kriging, volume variance corrections and conditional simulation studies.

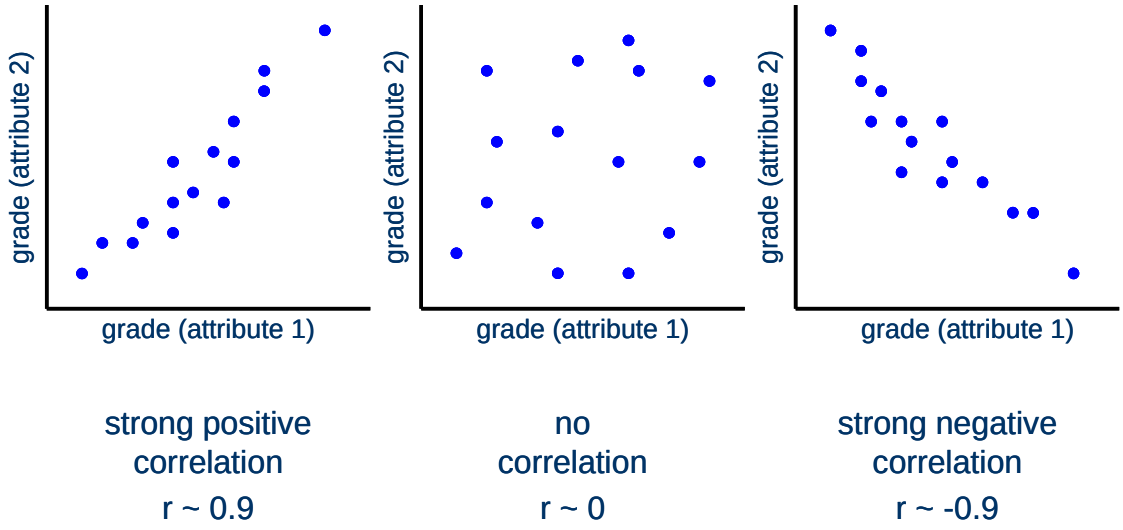
Multivariate statistics

When working with more than one grade attribute it is useful to look at multivariate statistics to determine if a relationship exists between the attributes. This information can be used to aid domaining and to determine which attributes can be estimated inside the same domains and which will require separate domains. It is also useful for variography as highly correlated attributes will have similar variability and behave in a similar fashion.

A useful tool for examining relationships is the scatterplot. A scatterplot directly compares paired data (Figure 3.23) and the degree of scatter or spread of results on the graph gives a visual indication of the correlation between the attributes.

Pearsons correlation coefficient can also be calculated to quantify the relationship between attributes (Figure 3.23). A correlation coefficient of 1 indicates a perfect positive correlation while -1 indicates a perfect negative correlation. Commonly a table is produced detailing the correlation between all attribute combinations.

Figure 3.23 Scatterplots and correlation coefficients



The correlation coefficient only measures linear correlations between attributes. Figure 3.24 shows examples where a clear non linear relationship exists between two attributes that results in a low correlation coefficient (left and centre examples). In the third (right) example, the presence of outliers reduces the correlation coefficient.

It is important to look at the scatterplots as well as the correlations to obtain a proper understanding of the relationships between attributes.

Figure 3.24 Scatterplots and correlation coefficients – non linear correlations

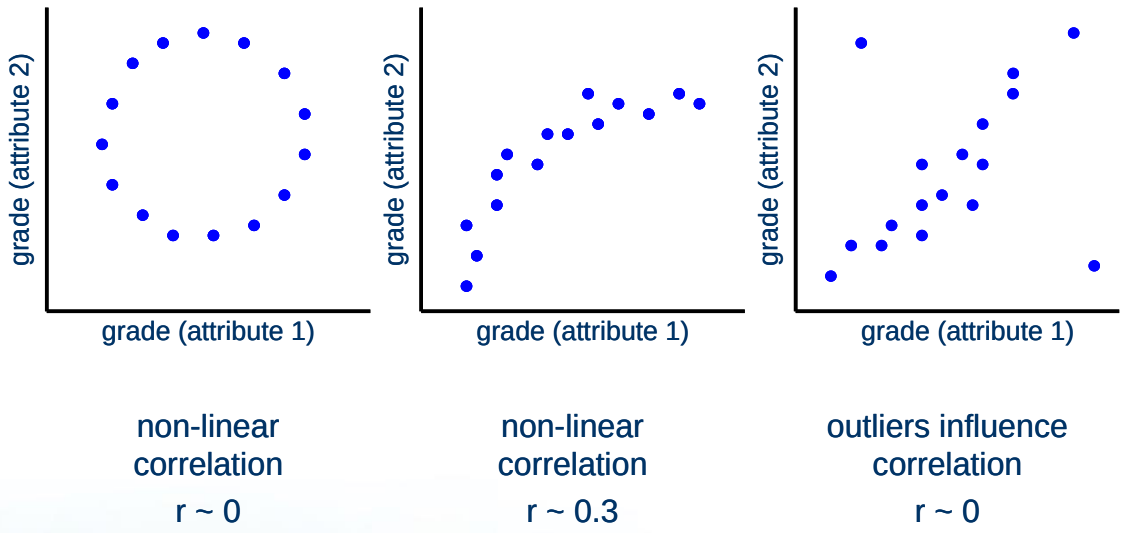
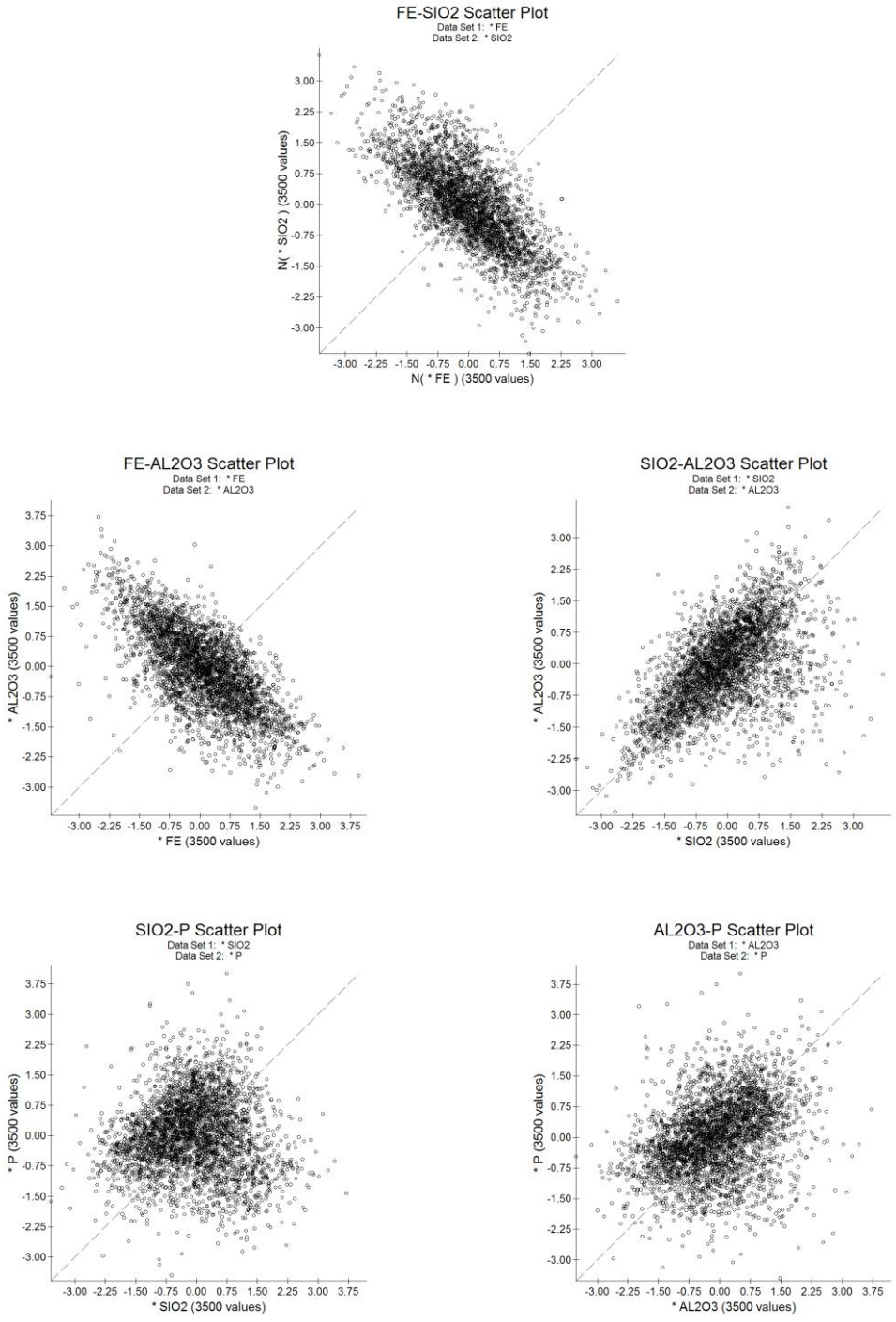


Figure 3.25 shows a case study example of scatterplots and correlations for four attributes. Iron has a strong negative correlation with silica and alumina and the silica and alumina are positively correlated. Phosphorous is not strongly correlated with any of the other attributes.

Figure 3.25 Case study showing multi element analysis



	Fe	SiO_2	Al_2O_3	P
Fe	1	-0.72	-0.69	-0.20
SiO_2		1	0.55	-0.01
Al_20_3			1	-0.32
P				1

Dealing with skewed populations

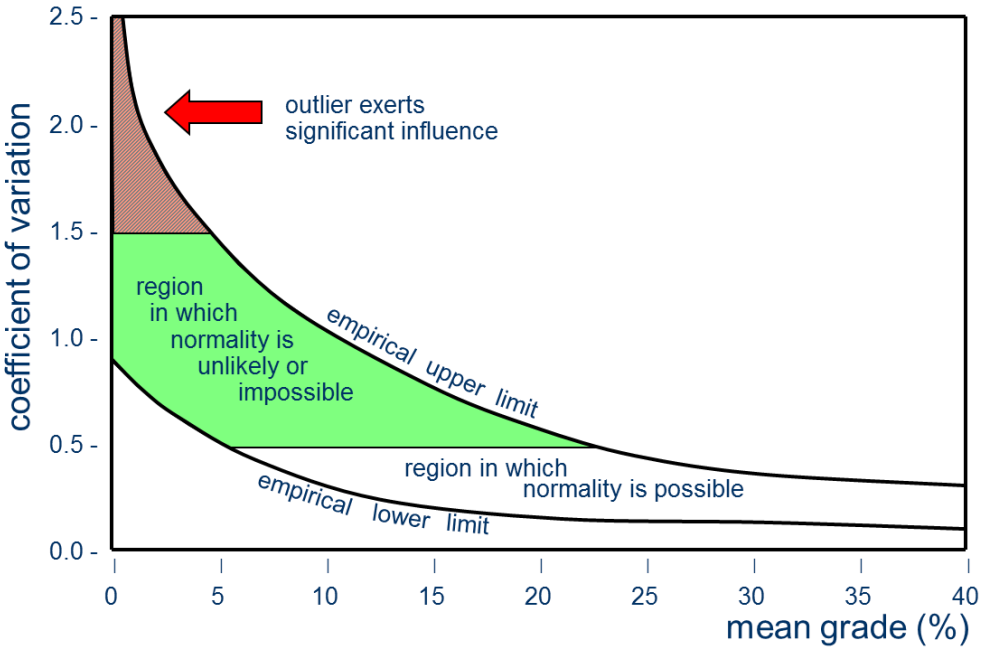
Skewness needs to be understood and managed during resource estimation. The coefficient of variation provides a tool for determining how skewed the data is.

For near normal distributions the coefficient of variation is less than 0.5. When the coefficient of variation is greater than 0.5, the distribution is unlikely to be normal (Figure 3.26). As the coefficient of variation rises the sample data is more skewed and contains increasing numbers of very high (outlier) values.

The impact of these outlier grades on the data statistics is to bias the mean towards the outlier grade and to inflate the variance and standard deviation, particularly when the population is only represented by a relatively small dataset. This is almost always the case during estimation when a small set of data (typically the closest say 10-40 samples) is selected to estimate the grade of a block. If the data is positively skewed, then it is likely most of the samples will be relatively low grade and a small number of samples will have relatively extreme grades. The estimated grade will be biased by the extreme grade, which may not be a true reflection of the underlying block grade. This means it becomes harder to produce reasonable estimates of the population characteristics.

Skewness can be managed during estimation by the use of domaining, top cuts (Section 3.4), indicator kriging (section 4.4.8) or simulation (section 6).

Figure 3.26 Skewness and the coefficient of variation (Wellmar, 1998)



3.3.2 Estimation domaining

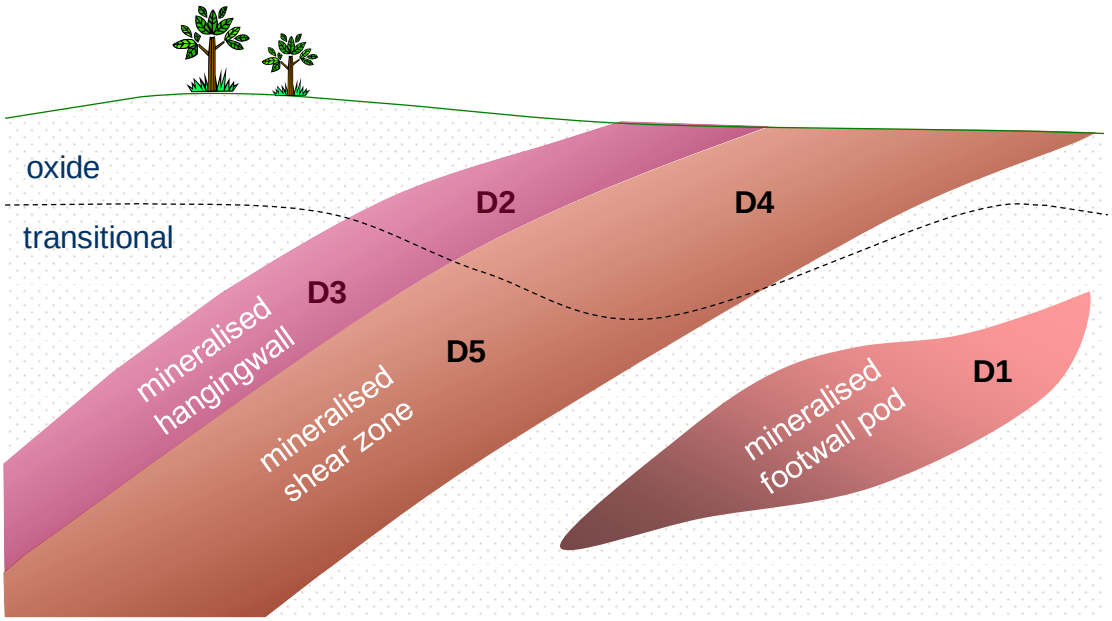
An estimation domain (Figure 3.27) is defined as a three dimensional volume delineating the spatial limits of a domain of stationarity. This means that:

- It forms a single statistical population.
- The mean and variance are consistent throughout the domain.
- It is geologically homogeneous.
- It has a single orientation of grade continuity.

The usual method of defining estimation domains is to start with all possible combinations of the geological controls (for example, mineralisation, weathering and structure) and compare the statistical populations for each sub-domain. Statistical populations that are similar can be combined for variography and estimation unless there is a geological reason for separating them, for example, they are spatially distant. Section 3.3.3 discusses methods and tools for comparing the sub-domain grade populations.

Clear domaining almost always leads to simpler variography and estimation. Poor domaining results in obscured continuity in the variograms and incompatible variogram models for estimation.

Figure 3.27 Estimation domaining based on geological interpretation



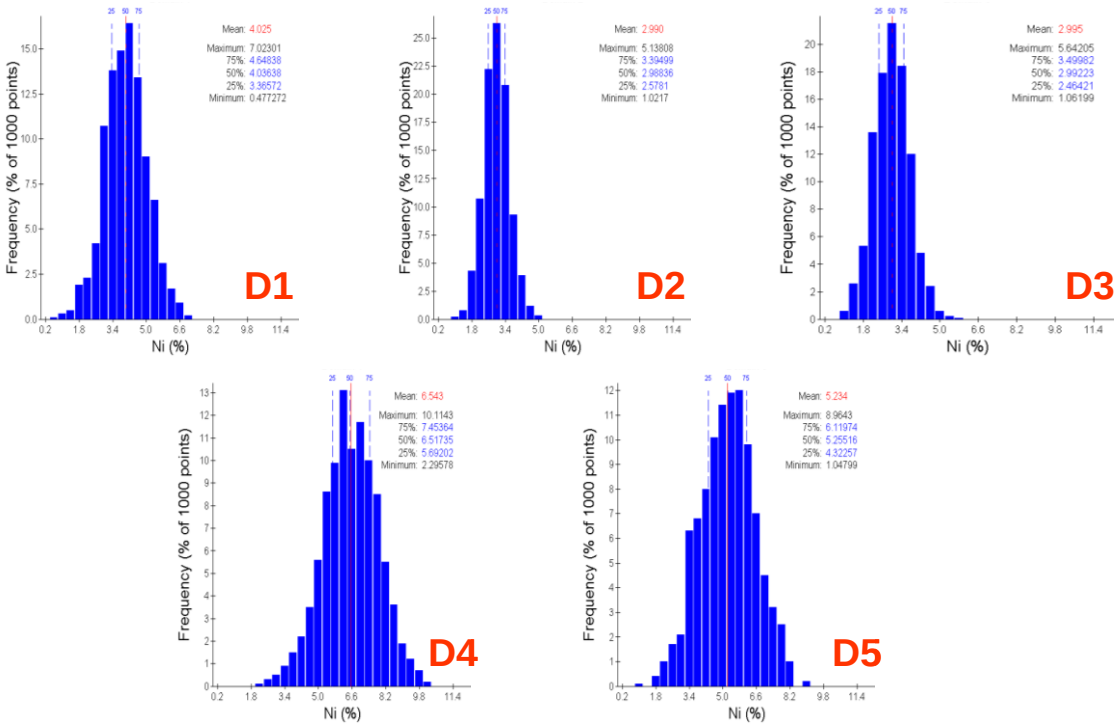
Verifying domains

Domain validation should be carried out before finalising the estimation domains. The data within each domain needs to be checked to ensure that the assumption of stationarity is met.

If working with multi-elements, make sure the domains are validated for all attributes as a domain that is appropriate for one attribute may not be appropriate for all attributes.

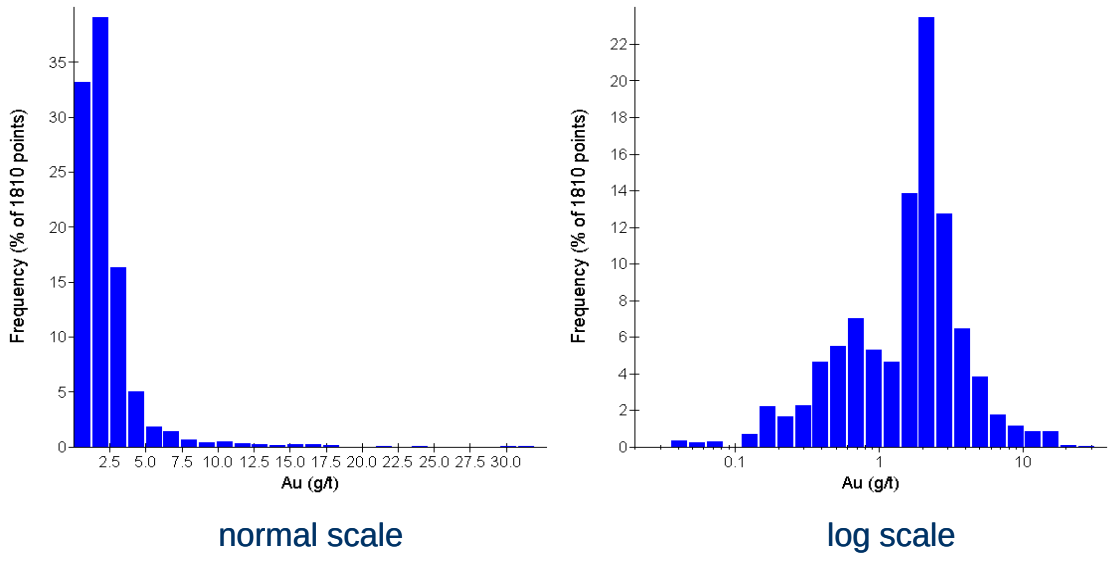
The main tools for domain validation are histograms and log probability plots. Figure 3.28 shows histograms for the five sub-domains illustrated in Figure 3.27. The histograms all show reasonably smooth distributions, indicating that the grades are from single statistical populations.

Figure 3.28 Case study showing histograms used to validate single grade populations



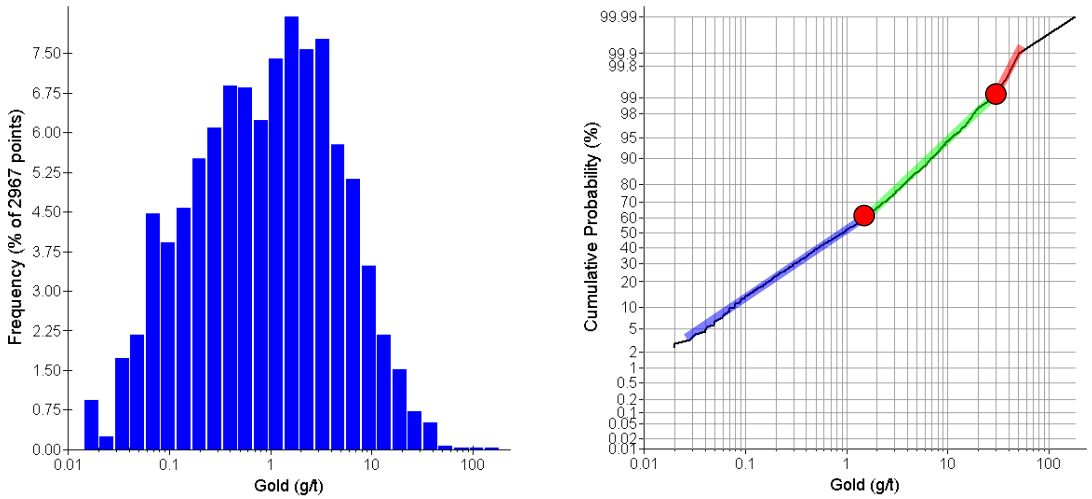
For positively skewed data, such as gold, mixed populations are usually more evident when the histogram is plotted on a log scale as illustrated in Figure 3.29.

Figure 3.29 Case study showing mixed positively skewed population in normal and log scale



Mixed populations can sometimes be obscured in a histogram due to overlapping statistical populations. They are typically more evident on a probability plot where mixed populations show up as inflection points. This is illustrated in Figure 3.29 where three statistical populations are evident on the log probability plot.

Figure 3.30 Case study showing mixed populations on a log histogram and log probability plot



histogram log probability plot

Looking at the scale on the y-axis (probability or proportion of data) will indicate how much of the data is in each statistical population. Note that inflections at the top end of the graph can reflect a very small portion of the data. In these instances this population change may be due to high grade outliers, the treatment of which is discussed in Section 3.4.

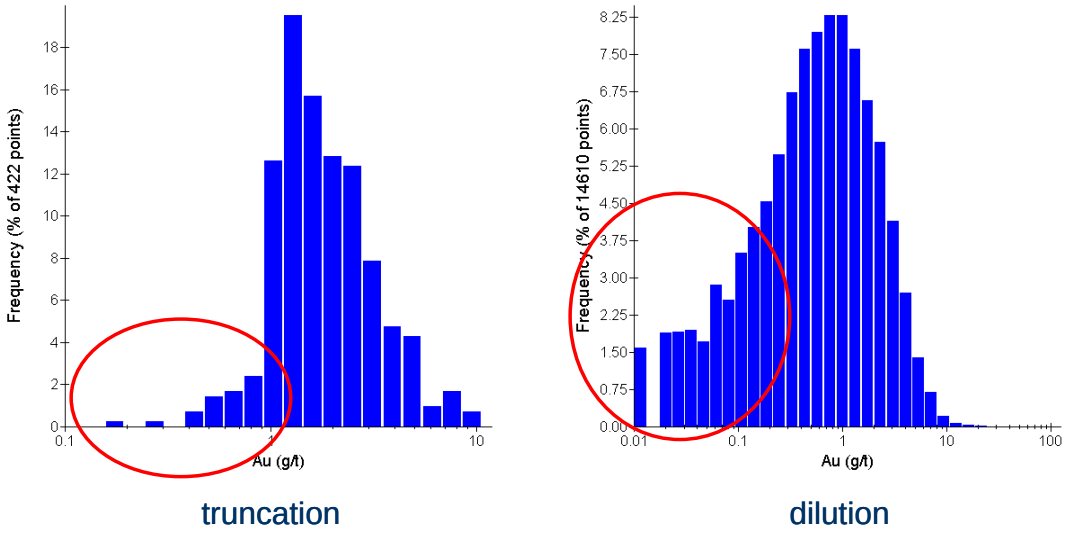
Where histograms or probability plots indicate the presence of more than one statistical population, the populations should be separated if they are spatially distinct. An easy way to do this is to pick the grade at the inflection points between the statistical populations and colour code the data above and below these grades. If the data above and below the inflection appear to be spatially distinct, then a geological reason should be identified by interrogating the geological logs. The domains should be re-defined to separate out the mixed populations. If the populations are spatially integrated then an indicator approach should be adopted.

The inflection points on histograms and probability plots can also be used as an aid to defining a grade cut-off for interpretation, however, there is usually overlap between two statistical populations and the inflection point grade cannot be treated as an exact cut-off. Use the inflection point grade as a guide for a nominal cut-off and try to find the geological reason for the change.

The incorrect use of grade cut-offs can lead to poor estimates. The histogram is a useful tool for identifying whether a grade boundary is reasonable. Figure 3.31 (left) shows an example where a cut-off has been used which is higher than geologically or statistically warranted. The low grade portion of the population has been truncated and the estimate will tend to be overestimated.

Conversely, Figure 3.31 (right) shows an example where a cut-off has been used which is too low. In this instance there is low grade dilution occurring which could result in underestimation.

Figure 3.31 Case study showing histograms illustrating the result of inappropriate grade cut-offs

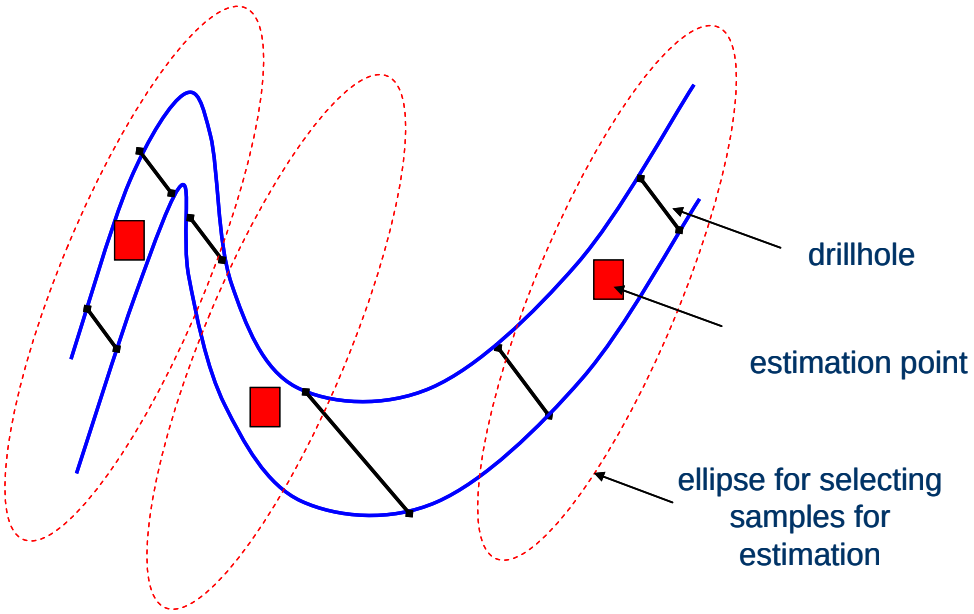


Orientation changes

Each domain should have a consistent orientation of continuity. Failure to deal with changes in orientation will result in inappropriate orientations being used to select samples for estimation as well as poor variography.

Figure 3.32 illustrates a domain with folded stratigraphy where the orientation of the ellipse used to select the samples is not changed.

Figure 3.32 Orientation changes

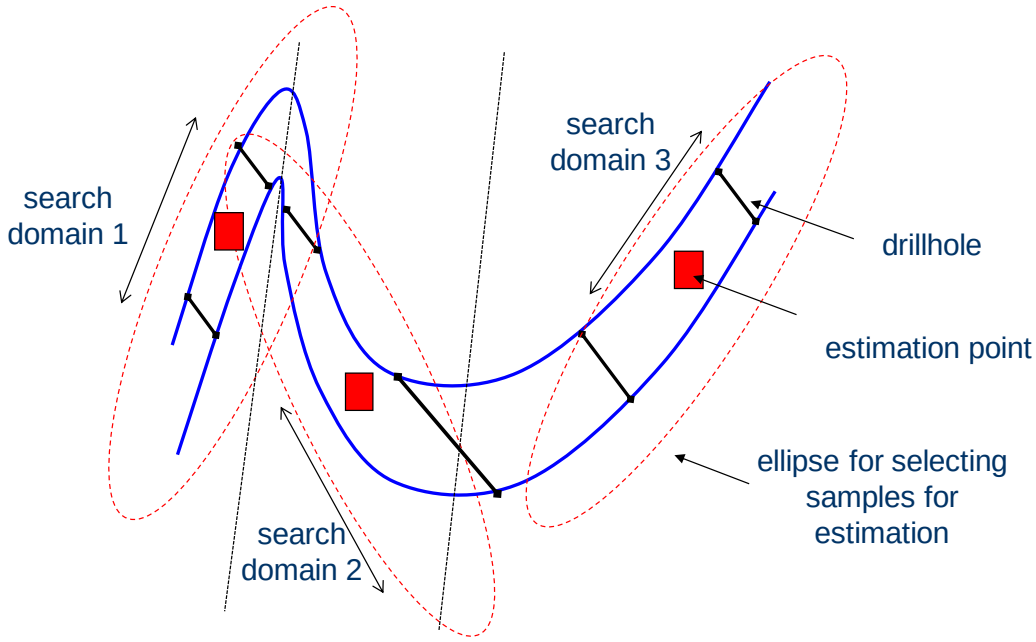


There are several options for dealing with orientation changes, including:

- Orientation or search domains.
- Moving search.
- Unfolding.

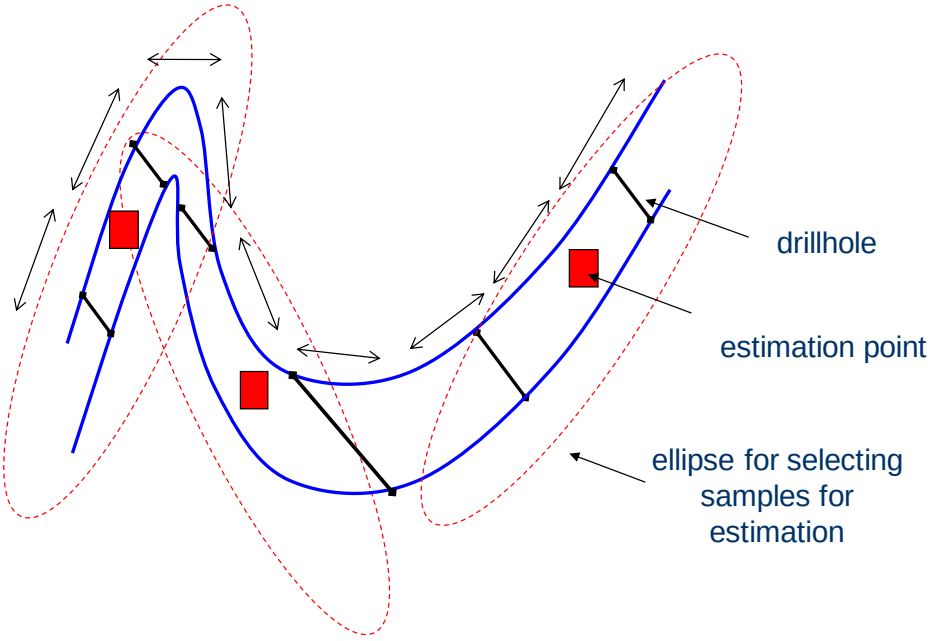
Orientation domains are created by splitting a domain at each change in orientation and independently carrying out variography and estimating each of these sub-domains. The boundary between orientation domains is generally treated as soft, meaning that the data on both sides of the boundary are used for estimation. The change in orientation can result in the wrong samples being selected for estimation due to the folding of the stratigraphy (Figure 3.33).

Figure 3.33 Orientation changes – orientation domains



Moving search estimation involves estimating orientations into the model and using this information to locally adjust the search ellipse and variogram orientations (Figure 3.34). The area of highest confidence with a consistent orientation should be used to define the variogram.

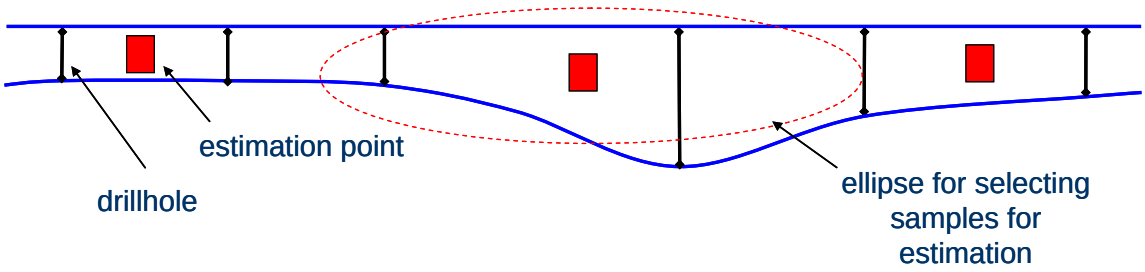
Figure 3.34 Orientation changes – moving search



Another option is to unfold the data so that it can be treated as belonging to a single domain (Figure 3.35). Unfolding involves relocating the data into pre-folded space so that the spatial relationship between data points is not impacted by the folding (assuming that this is geologically appropriate and that mineralisation pre-dates folding). Variography and estimation is then carried out in unfolded space.

Unfolding is useful in structurally folded deposits as well as stratigraphic or stratiform deposits such as nickel laterite and bauxite where the mineralisation tends to be flat lying and undulating.

Figure 3.35 Orientation changes – unfolding



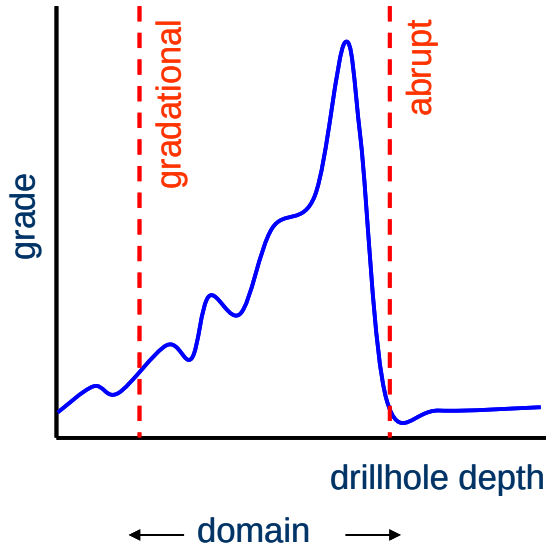
Boundary analysis

It is important to understand the nature of the boundaries between domains. If domain boundaries are gradational then data from the adjacent domains should be used during estimation (soft boundary). If there are abrupt boundaries then estimation should be restricted to only use the data within that domain (hard boundary).

A one-way soft boundary is sometimes used where a high grade core is estimated using the data from that domain plus the surrounding lower grade domain while the lower grade domain is estimated using only the lower grade data. This reflects a situation where a low grade mineralising event is followed by a later high grade mineralising event.

With a small dataset the nature of the domain boundaries can be assessed by visually looking at each drillhole that cuts across the domain. A graph of grade versus drillhole depth is the simplest way to do this (Figure 3.36). However be aware of the orientation of the drillhole data compared to the domains. If the drillholes are not roughly perpendicular to the domains the results can be misleading.

Figure 3.36 Boundary analysis using downhole graphs

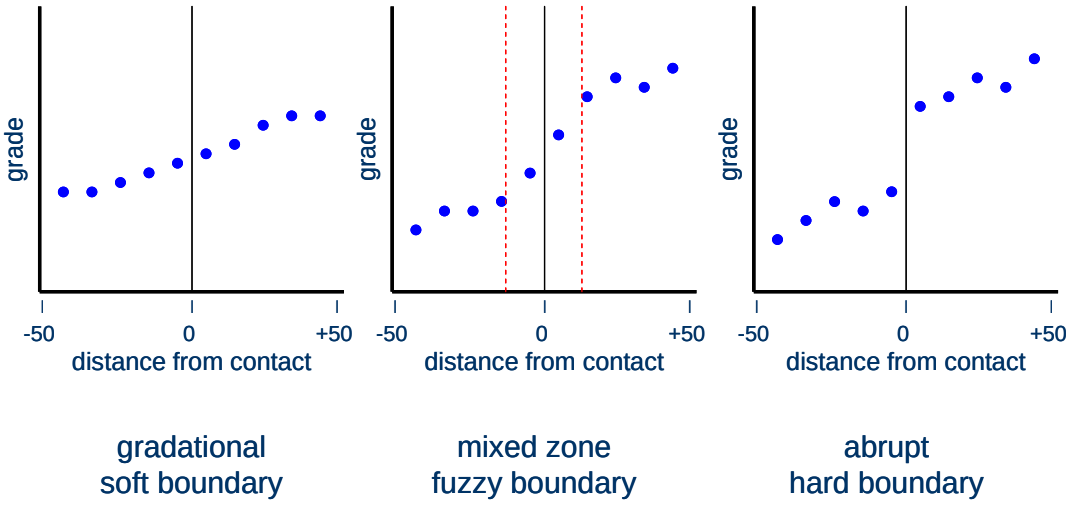


With a large dataset the above method is impractical. In this instance a contact analysis can be carried out. This involves graphing the average grade with increasing distance from the domain boundary. The average grades can be calculated by incrementally expanding the wireframes or manually by coding the samples based on distance from the domain contact.

Figure 3.37 illustrates three examples of contact analysis graphs. The following comments are a guide as to how the boundaries might be treated in each of these cases:

- Left – soft, gradational boundary; use all data for estimation.
- Middle – zone of mixing, almost gradational; use a fuzzy boundary where data up to a certain distance away from the boundary are allowed.
- Right – hard boundary; only use the individual domain data for estimation.

Figure 3.37 Contact analysis graphs



3.3.3 Comparing statistical populations

There is often cause to compare two datasets where the samples are not necessarily paired. For example:

- Comparison between different data sources to check for bias due to methodology or different support (for example, reverse circulation versus diamond drillhole data, exploration versus grade control or historical versus current drillhole data).
- Comparison between domains to identify whether they form part of the same statistical population. If two domains have similar statistical properties and it is geologically appropriate, they can be combined for variography and estimation.

These comparisons can be achieved using Q-Q plots where the percentiles from each dataset are plotted against each other (Figure 3.38). If this plot forms a straight 1:1 line, then the datasets have the same distribution. Deviations from the 1:1 relationship indicate differences in distributions.

Figure 3.39 illustrates three case studies using Q-Q plots to compare drilling programs, domains and drilling types respectively.

Figure 3.38 Q-Q plot for comparing grade populations

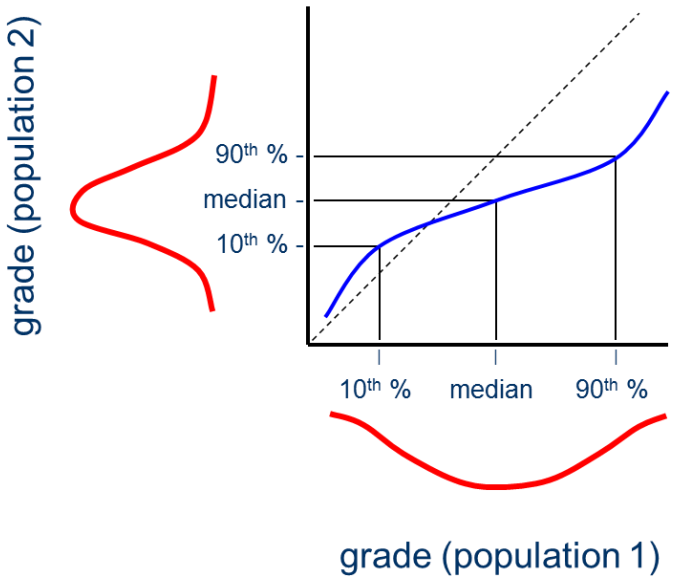
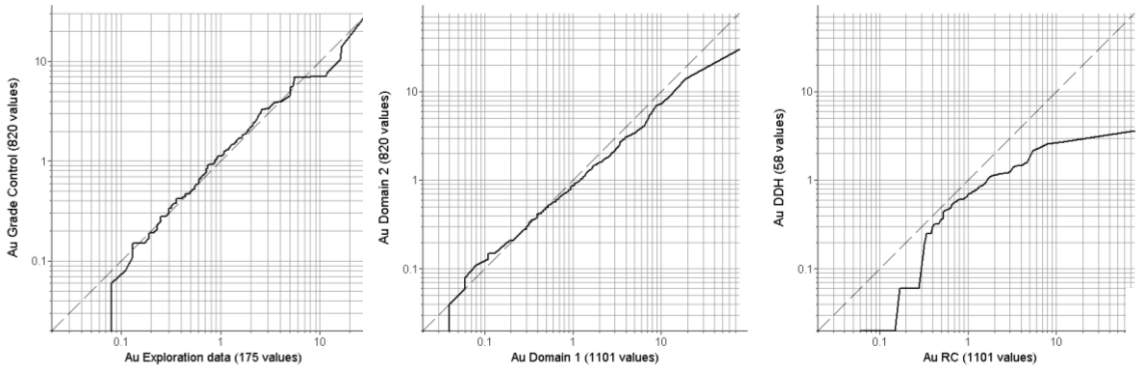


Figure 3.39 Case studies of Q-Q plots



exploration versus grade control

domain 1 versus domain 2

reverse circulation versus diamond

When different data types are compared, it is important to delineate common volumes so the comparison is not biased. In the case of domain comparison a common area is not required as the assumption is being made that volumes from which the datasets are sourced are statistically similar and the Q-Q plot is being used to test this assumption.

As more datasets are compared the number of Q-Q plots used for comparisons between individual datasets increases. In this instance a box and whisker plot is useful as it provides a quick visual aid to determining which domains or datasets are not comparable.

A box and whisker plot summarises the statistics for all datasets on a single graph (Figure 3.40). A box and whisker is created for each dataset. The whiskers define the range in sample values (spread between minimum and maximum value); the box defines the inter quartile range (or middle 50%) of sample values. There is a bar in the box to indicate the median sample value and the mean grade is usually highlighted in the box and whisker plot.

Those domains or datasets that appear to have similar statistics can then be compared more thoroughly using a Q-Q plot.

Figure 3.41 shows the statistical population comparison carried out for the five sub-domains discussed previously (Figure 3.27). In this instance, the box and whisker plot indicates that domains D2 and D3 are similar. The Q-Q plot of these two domains shows that there is some difference in the distributions, particularly at lower grades.

Figure 3.40 Box and whisker plot for comparing grade populations

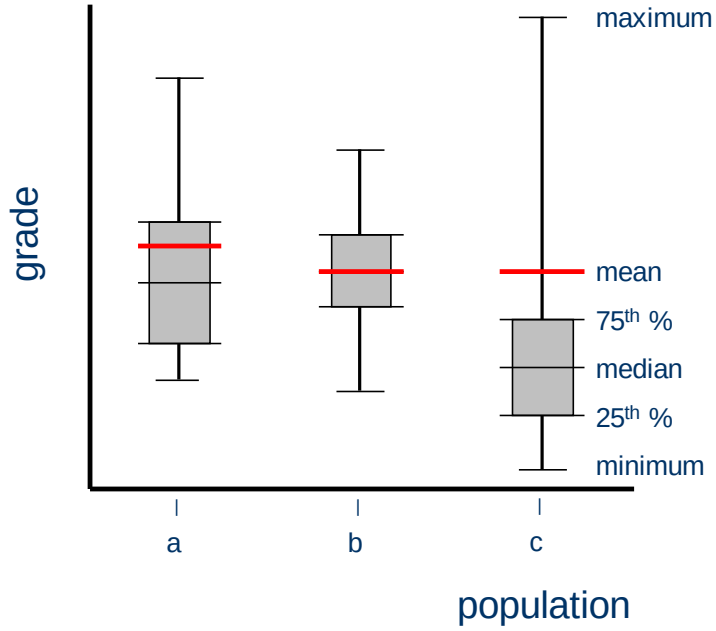
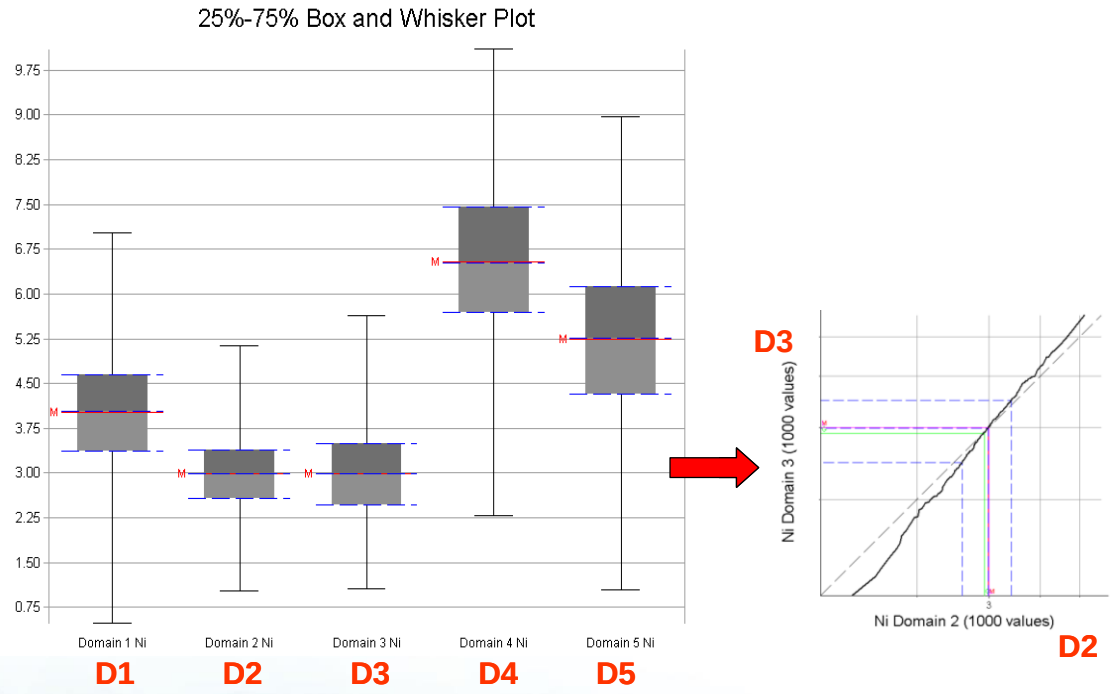


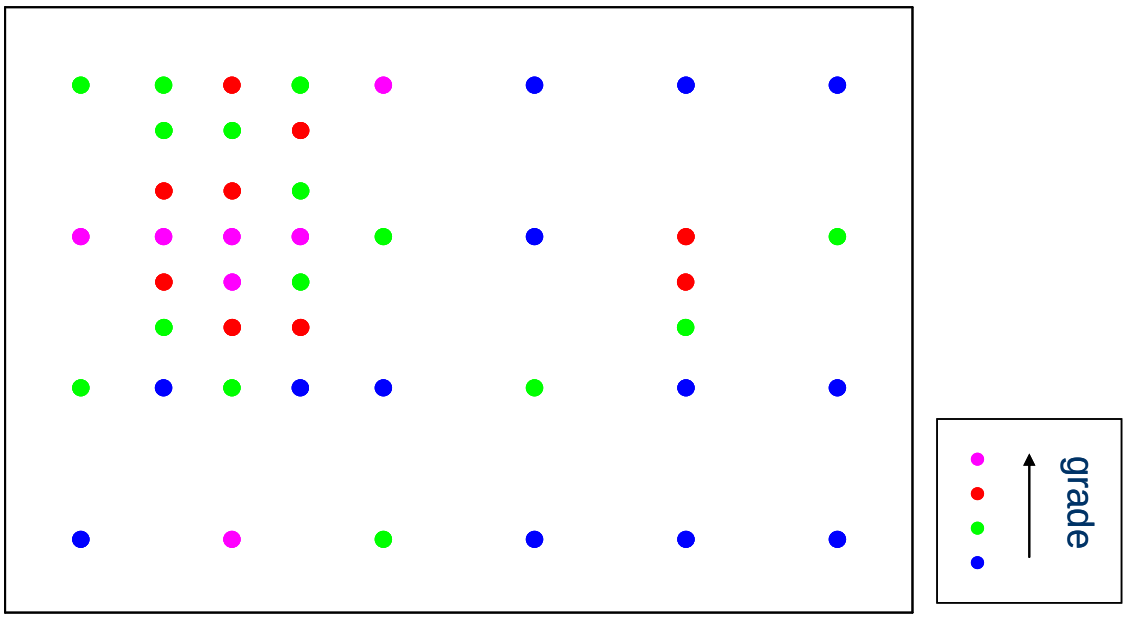
Figure 3.41 Case study showing comparisons of sub-domains



3.3.4 Declustering

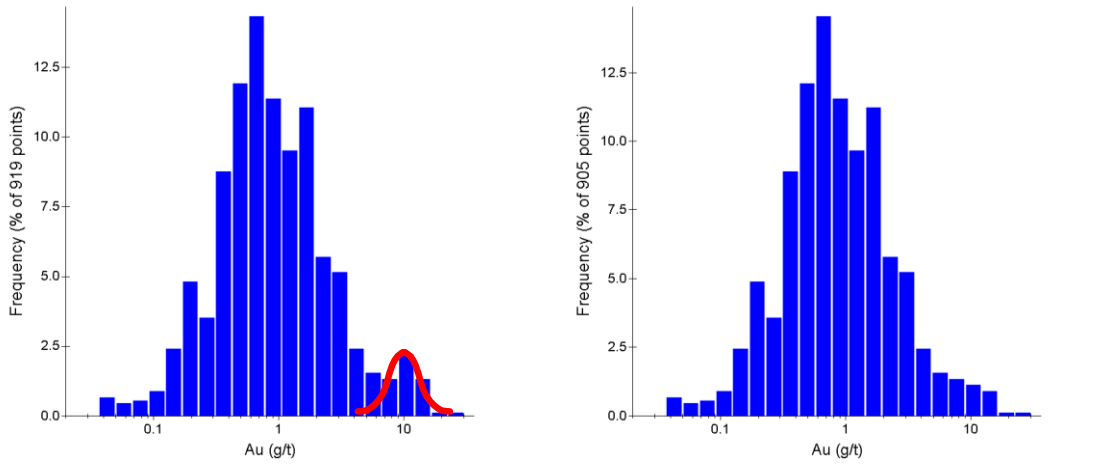
Clustering is caused by irregular sampling of a volume through “Directors’ Holes”, fan drilling or infill drilling. Clustering results in extra samples (usually high grades) in the dataset used for statistical analysis (Figure 3.42).

Figure 3.42 Clustered data



Clustering of samples within a high grade area can manifest itself in the histogram as mixed populations (Figure 3.43). The calculated mean and variance can also be biased by the additional high grade sample values.

Figure 3.43 The impact of high grade clustering



clustered data
mean 1.67

declustered data
mean 1.51

In order to remove any bias due to clustering, declustering is carried out on the data. The process of declustering is a preparation step for:

- Validation of the estimate (comparison of the means).
- Assisting in preparation for variography. Declustering can change the mean and variance and can affect the variogram.
- Simulation (where the sample histogram must be honoured).

Note that declustering is not necessary for estimation as the estimation processes handle data clustering (section 4.4.5).

There are many ways to decluster data, each giving different results:

- **Interactive filtering** involves the removal of specific drillholes or samples for the statistical analysis of the dataset. These drillholes or samples are retained for variography and estimation.
- **Polygonal declustering** involves the formation of polygons around each sample using the vertices equidistance between each surrounding sample point. The area defined by each polygon is then used to weight the samples (Figure 3.44).
  - Bad edge effects can occur using this method if there are large unsampled areas on the edges. The unsampled edges result in large polygons and hence large weighting being applied to these samples. The reverse effect can occur if the edge blocks are too small (Figure 3.45).

Figure 3.44 Polygonal declustering

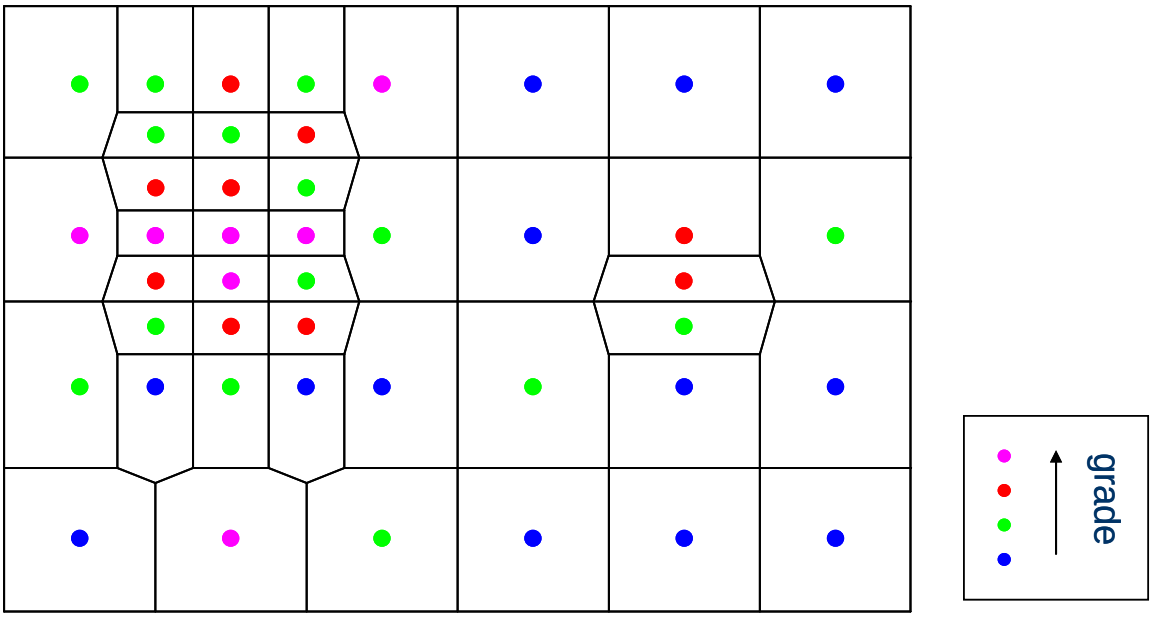
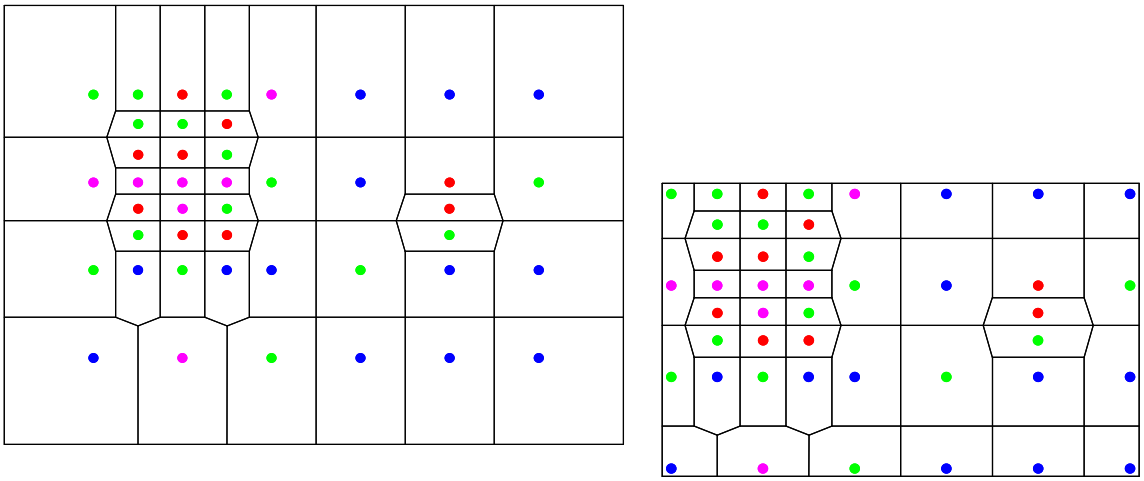
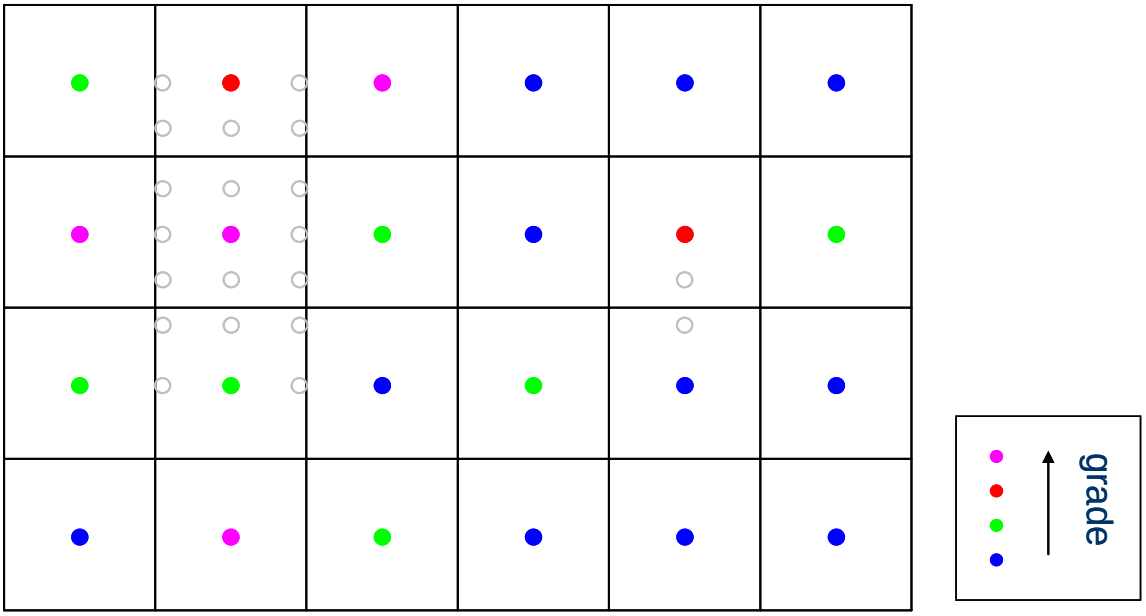


Figure 3.45 Polygonal declustering – edge effects



For **nearest neighbour declustering** (normalisation) a grid of cells is placed over the data and only those samples that are closest to the cell centroids are maintained for statistical analysis (Figure 3.46). Typically only one sample per cell is maintained, but it is also possible to maintain only one drillhole per cell. This method is not recommended as it removes data and the selection of the sample is dependent on the origin and cell size when defining the cells.

Figure 3.46 Nearest neighbour cell declustering



- **Cell weighting** declustering involves placing a grid of cells over the data (
- Figure 3.47). Each cell that contains at least one sample is assigned a weight of one. That weight of one is distributed evenly between the samples within each cell. Cell declustering, after investigating various cell sizes and origins, is the recommended method of declustering as all samples are considered when determining the average.
  - To test the impact of the declustering cell size, the weighted average grade should be calculated for a range of cell sizes. The cell size where the weighted average grade stabilises is the optimum cell size (Figure 3.48). In most cases the clustering is in the higher grade areas and increasing the declustering cell size will result in a decreasing grade out to an optimum size at which time the grade will stabilise or increase again. Note that sometimes clustering is in lower grade areas due to access or mining issues. In this case the pattern will be reversed.
  - The nominal drillhole spacing is a good starting point for testing cell sizes but test a range of sizes. When reviewing the results, think about scale; what is a material difference?

Figure 3.47 Cell weighting declustering

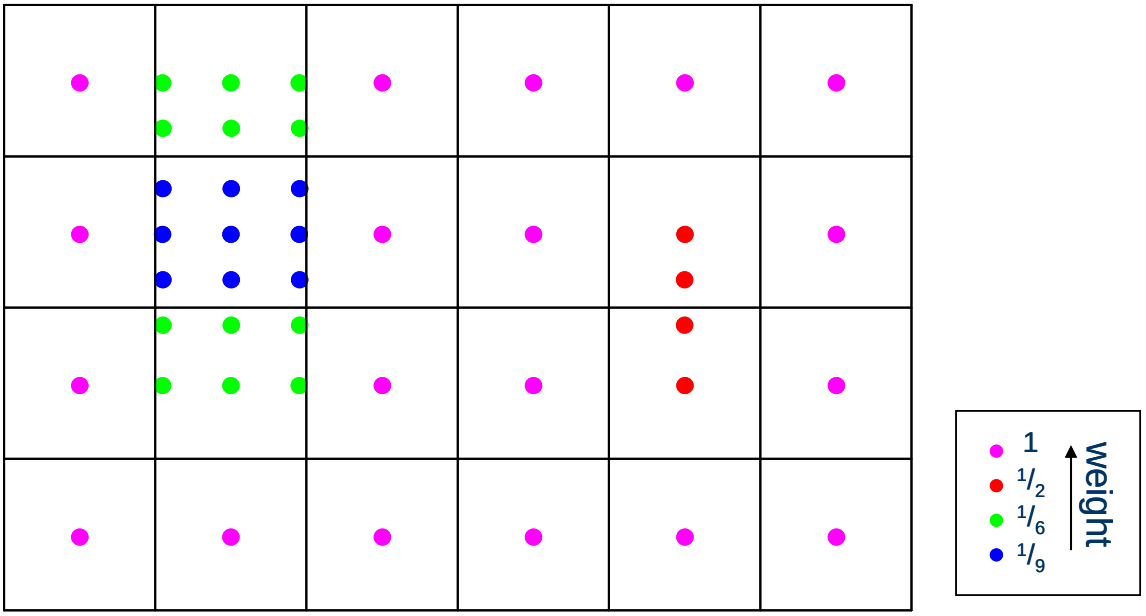
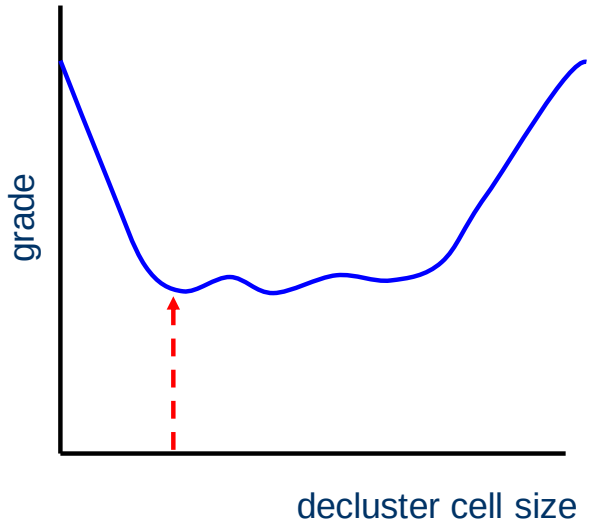


Figure 3.48 Cell weighting declustering – optimising the cell size



There is the potential for artifices in the declustering weights on the edges of domains as illustrated in Figure 3.49. The impact of these edge effects can be assessed by testing a number of offsets on the origin of the cells.

If the data is on a regular grid with no clustering, there is no need to decluster.

Figure 3.50 provides some examples of clustered data in open pit and underground scenarios.

Figure 3.49 Declustering weight artifices

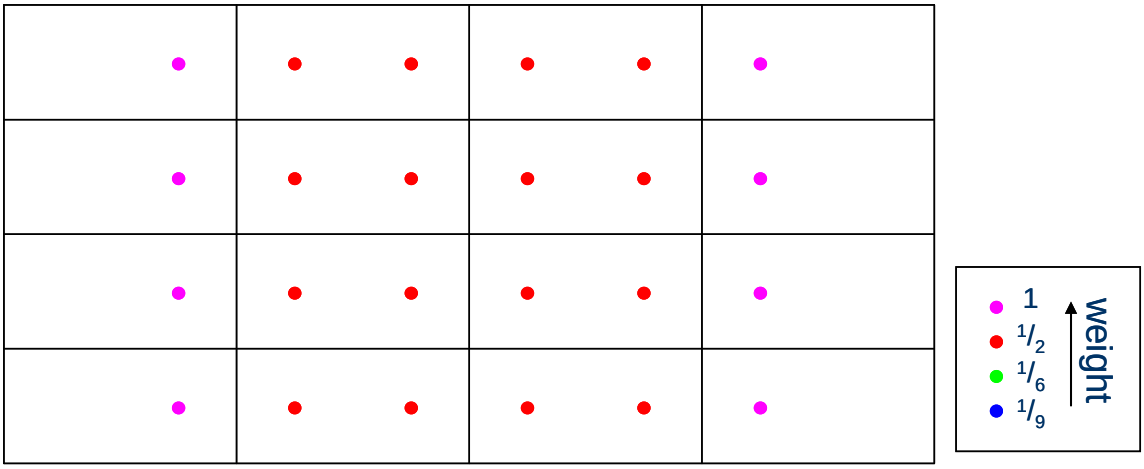
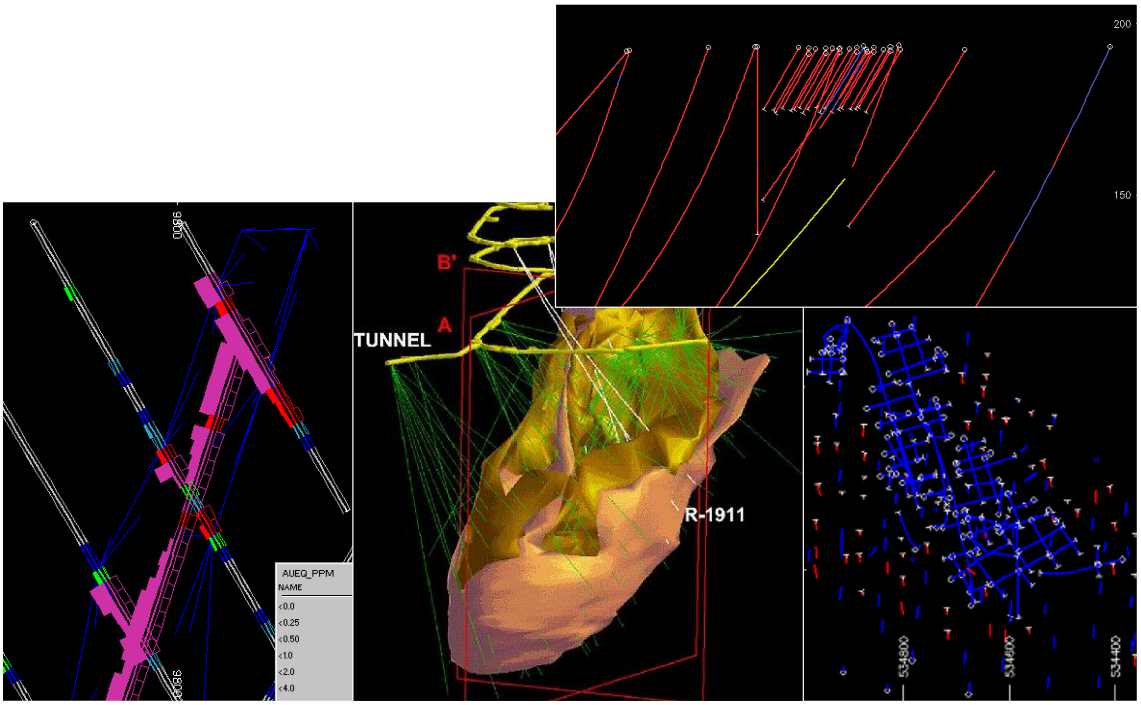


Figure 3.50 Clustering examples



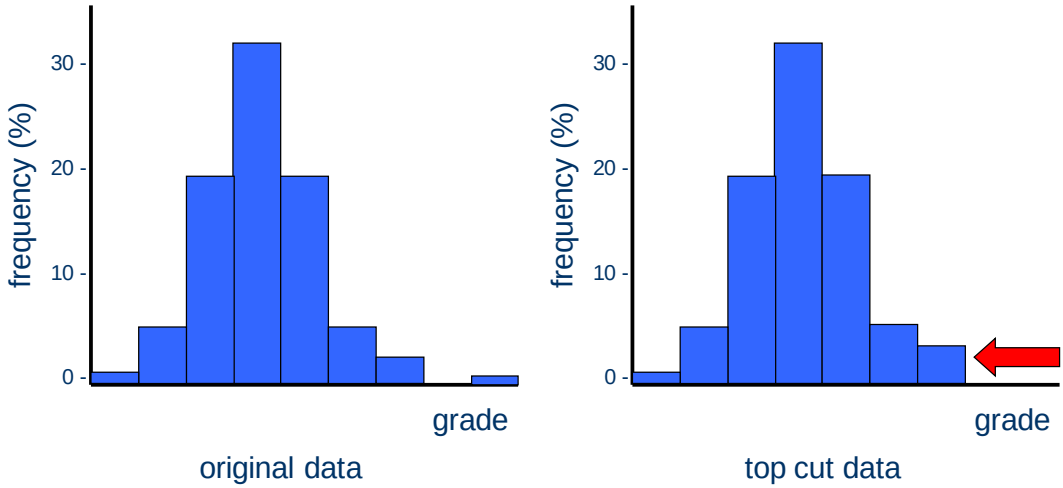
3.4 Top cutting strategies

An outlier is an extremely high or extremely low value of a variable which lies outside the range of values expected based on the distribution of the rest of the data. In reality outliers are one of two things; an error or part of a different statistical population.

A note on nomenclature; top cuts in this manual refer to the practice of resetting outlier grades to a lower grade. In some countries this practice is referred to as top capping and top cutting refers to the removal of outlier grades. The removal of grades is not recommended unless the outlier is thought to be an error or geologically unrepresentative of the mineralisation (for example native copper in oxide copper deposits).

The application of top cuts (Figure 3.51) can prevent overestimation in small sub-sample sets due to disproportionate high grade outliers. Every estimation method limits the number of samples used per block estimate. Typically 10 to 40 samples are used to estimate the grade in any block of a resource model. Whenever the sub-sample set contains an extreme grade, this extreme grade will overly influence the estimated grade. The influence of the extreme grades is controlled by resetting extreme grades to a more realistic grade for estimation.

Figure 3.51 Top cut application

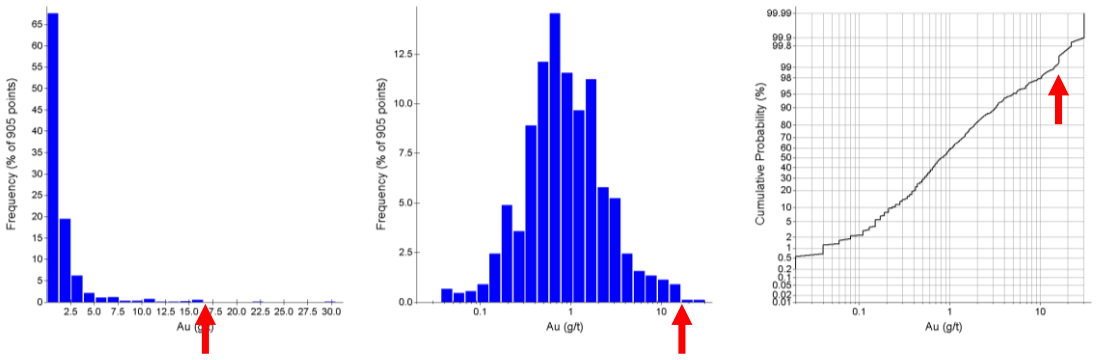


Although there is no theory to justify an analyst's choice of top cut, the coefficient of variation is a useful guide to decide on the degree of top cutting required. Top cuts should be considered for positively skewed distributions with coefficients of variation greater than 0.5. This should not be a hard and fast rule though and the population distribution should always be checked.

Tools for selecting appropriate top cuts include:

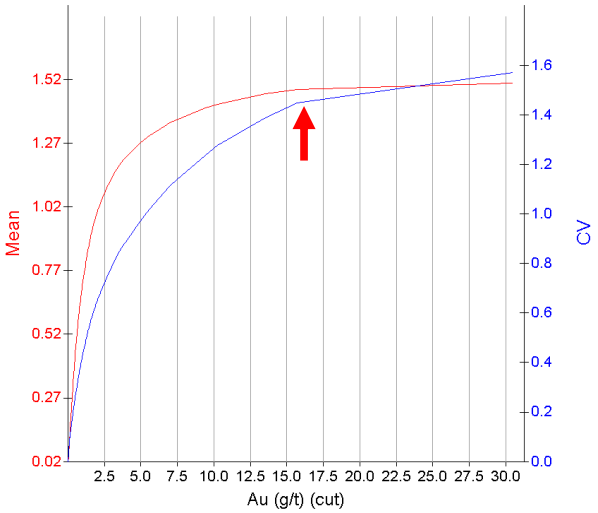
- Histogram and log probability plots – look for the point of distribution decay or disintegration (Figure 3.52).
- Mean and variance plots – examine the impact on the mean and coefficient of variation (or variance) with decreasing top cut (Figure 3.53). It is important that only outliers are cut. If the statistical population is extremely skewed and top cutting has a large impact on the mean grade, indicator kriging may be more appropriate.
- Reconciliation – production data and mining history are also useful when top cuts are evaluated. Consider what has worked in the past.

Figure 3.52 Case study showing point of disintegration used as a guide to top cutting



histogram log histogram log probability plot

Figure 3.53 Case study showing the impact of top cutting on the mean grade and coefficient of variation



mean and variance plot

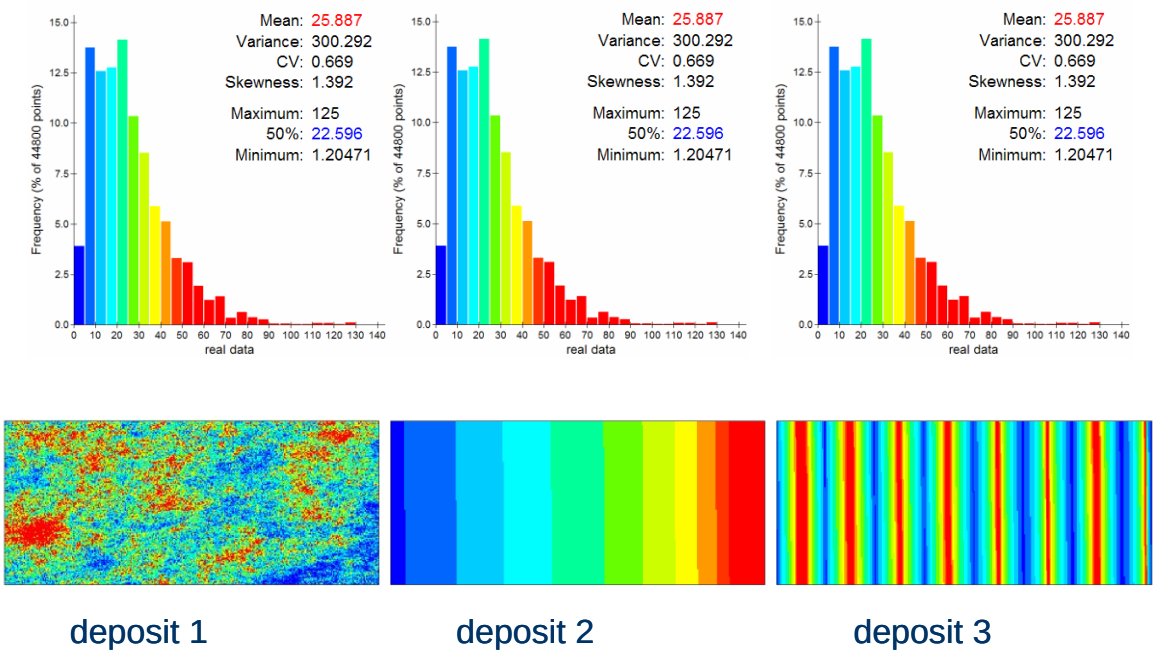
Once an appropriate top cut has been selected, look spatially to see where the outliers lie. If the outliers are close together then they should potentially be treated as a separate domain rather than top cut.

3.5 Spatial analysis (variography)

Consider the three examples illustrated in Figure 3.54. In each of these cases the histograms and statistics are identical, however spatially the sample value locations are very different.

Understanding how sample values relate to each other in space can help to infer possible similarities between known samples and points that have not been sampled. This information can then be used to generate an estimate of the sample value at unsampled locations.

Figure 3.54 Case study showing statistics and location plots for three deposits



Consider plotting the differences between the sample values against the separation distance between samples. Intuitively, samples further apart are more different from each other than samples close together.

Another way of presenting typical differences between samples is to look at the variability of samples for any given separation distance. A **variogram** is created by plotting the average variability for all sample pairs at a certain distance apart against that separation distance.

Figure 3.55 Variogram

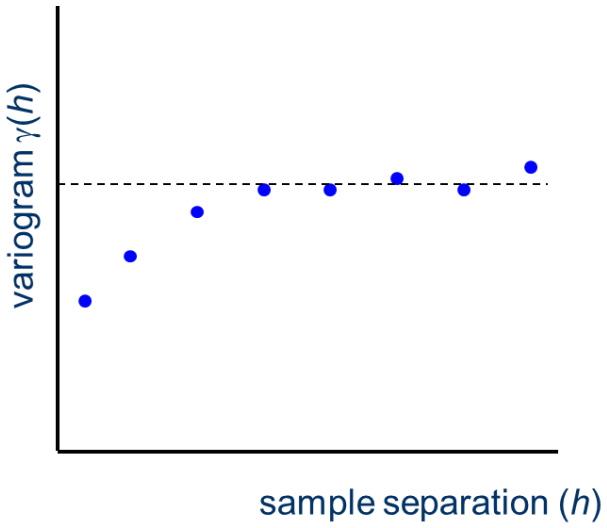
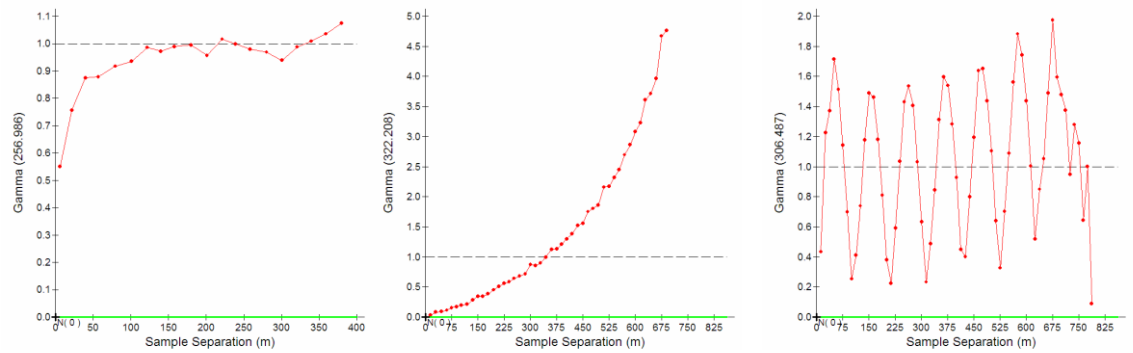


Figure 3.56 illustrates the variogram plots relating to each of the three cases looked at previously. It can be seen that even though the statistics and histograms are identical, the spatial relationships are very different in each case.

Figure 3.56 Case study showing variograms for three deposits



deposit 1 deposit 2 deposit 3

Variograms can be calculated either purely by separation distance or by separation distance and direction. If direction is not taken into account and all sample pairs at a given separation distance are used in the calculation of the average variability, it is referred to as an omni-directional variogram. If direction and distance are used to select sample pairs, then it is referred to as a directional variogram.

When calculating variograms, the separation distance is termed the **lag** or "*h*" (for example 10 m). When calculating directional variograms, "*h*" refers to the distance and direction vector (for example 10 m north-south).

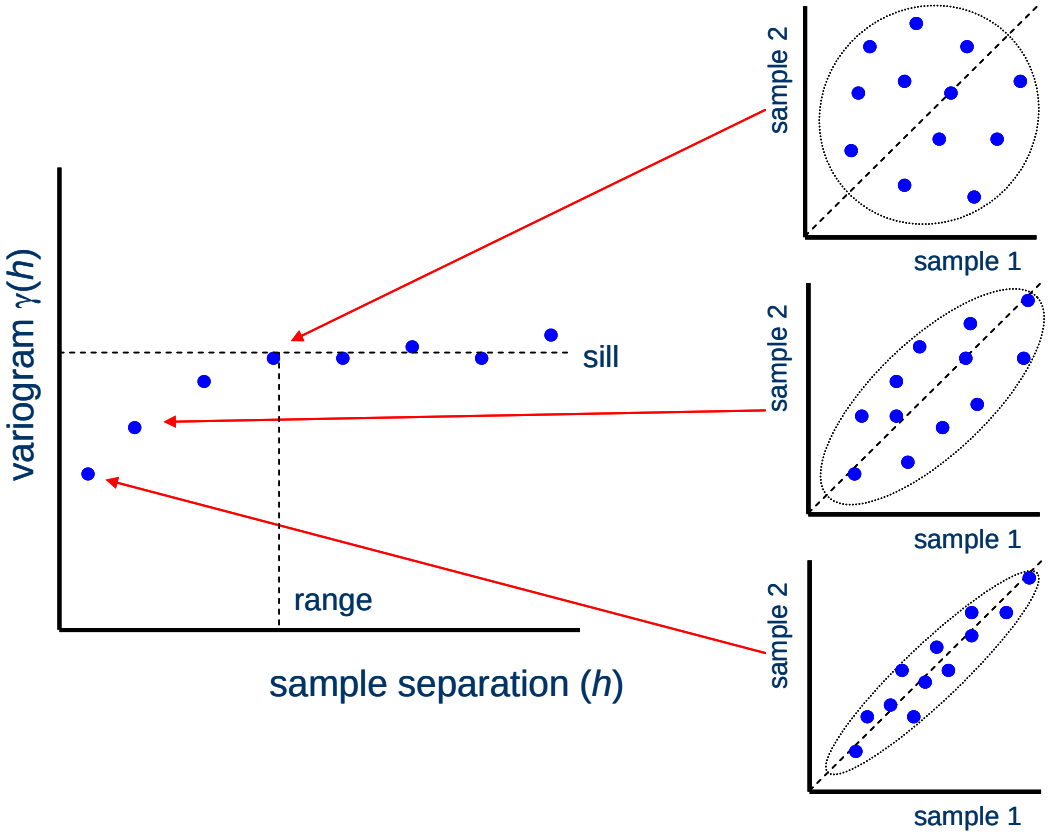
The gamma symbol (γ) is the standard symbol for variability in a variogram. On the variogram we plot $\gamma(h)$ being the average variability (or variogram value) of all sample pairs separated by vector "*h*". The average variability is calculated for a series of lags and plotted against lag distance to create a variogram plot.

Each point on the variogram can also be illustrated as a scatterplot of the sample pairs at that lag. These scatterplots are called h-scatterplots and are useful for reviewing what pairs make up the average value you are seeing on the variogram (Figure 3.57).

As the lag distance increases and the sample pairs become more different, the scatterplots show a poorer correlation and the corresponding average variability increases up to a point where the average variability becomes equal to the total data variance or **sill**.

The separation distance at which the sill is reached is called the **range** or range of continuity and indicates the distance at which there is no longer correlation between the samples.

Figure 3.57 Variogram and h-scatterplots



3.5.1 Calculating a variogram

A variogram value is calculated as half the average squared difference of all the sample pairs for a specific distance and direction. This is in effect measuring the average spread of the h-scatter plot for each lag.

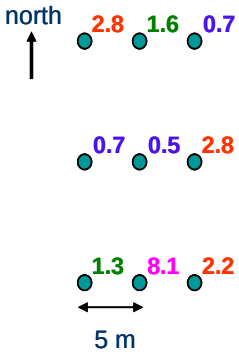
$$\text{Variogram } \gamma(h) = \frac{\text{sum of (sample value – sample value at vector h away)}^2}{2\ (\text{number of sample pairs collected for vector h})}$$

Note the similarity between the variogram equation and the variance equation. Variance is the average difference between the samples and the mean rather than paired samples. Halving the variogram scales it so that the variogram sill is equivalent to the total data variance[1].

Figure 3.58 illustrates the collection and calculation of variogram values for a 5 m east-west lag and a 10 m north-south lag using the nine samples illustrated.

[1] *In this manual we mean semi-variogram when we use the term variogram. Strictly speaking a semi-variogram implies the variogram has been scaled to the population variance - i.e. has been divided by "2" in the equation.*

Figure 3.58 Worked example - traditional variogram calculation

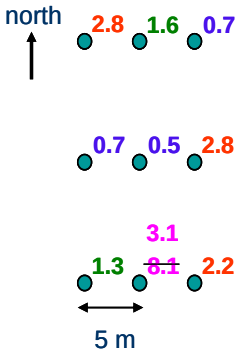


data	h = 5 m east-west	h = 10 m north-south
	$(2.8-1.6)^2$	$(2.8-0.7)^2$
	$+ (1.6-0.7)^2$	$+ (0.7-1.3)^2$
	$+ (0.7-0.5)^2$	$+ (1.6-0.5)^2$
	$+ (0.5-2.8)^2$	$+ (0.5-8.1)^2$
	$+ (1.3-8.1)^2$	$+ (0.7-2.8)^2$
	$+ (8.1-2.2)^2$	$+ (2.8-2.2)^2$
	88.63	68.51
	88.63 / (2 x 6)	68.51 / (2 x 6)
	$\gamma(h) = 7.39$	$\gamma(h) = 5.71$

3.5.2 Types of variograms

Consider the two cases presented in Figure 3.59. These are both the same with the exception of one grade which has been increased from 3.1 to 8.1. This one grade changes the variogram value from 0.97 to 7.39. Extreme values dramatically increase the measure of variance relative to distance, in a similar way to their effect on the variance and standard deviation calculations.

Figure 3.59 Worked example - the impact of extreme grades on variogram calculation



data	h = 5 m east-west	h = 5 m east-west
	$(2.8-1.6)^2$	$(2.8-1.6)^2$
	$+ (1.6-0.7)^2$	$+ (1.6-0.7)^2$
	$+ (0.7-0.5)^2$	$+ (0.7-0.5)^2$
	$+ (0.5-2.8)^2$	$+ (0.5-2.8)^2$
	$+ (1.3-8.1)^2$	$+ (1.3-3.1)^2$
	$+ (8.1-2.2)^2$	$+ (3.1-2.2)^2$
	88.63	11.63
	88.63 / (2 x 6)	11.63 / (2 x 6)
	$\gamma(h) = 7.39$	$\gamma(h) = 0.97$

There are number of different variogram types which are designed to reduce the impact of extreme grade outliers in highly skewed data. Most variogram types differ in either the way the data is transformed before the variogram calculation or in the way the difference between the grades is standardised.

Examples of the various types of variograms are presented below. Each type of variogram is based on the same formula as the traditional variogram discussed above.

- Traditional: uses raw grades in the variogram formula.
- Data transformation variograms:
  - Normal scores:

    Transforms the data to a Gaussian or normal distribution before variogram calculation (also called a Gaussian variogram). The variogram model must be back-transformed prior to use in estimation.
  - Indicator:

    Applies an indicator transform to the data prior to variogram calculation. Estimation is carried out on the indicator values so no back-transform is required.
  - Log:

    Applies a log transform to the data prior to variogram calculation. The variogram model must be back-transformed prior to use in estimation.

- Grade difference standardisation variograms:
  - Pairwise relative:

    For each pair of samples, divide by (half of (head sample + tail sample))[2].
  - General relative:

    Divide by (half of (mean of head samples + mean of tail samples)[2].
  - Madogram:

    Use absolute of difference instead of square of difference.
  - Covariance:

    Subtract (mean of head samples)*(mean of tail samples).
- Other variogram types:
  - Correlogram:

    Divide by (standard deviation of head samples)*(standard deviation of tail samples). This variogram measures the correlation rather than the variability between sample pairs.

For highly skewed populations, transforming the data prior to calculating the variogram can provide a clearer view of ranges of mineralisation continuity as the transformation removes the influence of the skewed tail of the population distribution. As a result of this process however, the variability is also reduced and in order to obtain a final variogram model the normal scores and log variogram models must be transformed back into traditional space prior to use in estimation. This is not relevant for indicator variograms as estimation is carried out using the indicator values.

The transformation and subsequent back-transformation process can potentially introduce artifacts into the variogram model therefore it is preferable to model the variograms without transformations if possible. However in highly skewed populations this is not always possible.

[2] *Head and tail samples refer to the first and second samples in a pair used for variogram calculation.*

Variograms which standardise the grade differences, such as the pairwise relative variogram, also reduce the variability. The problem here is that there is no way to adjust these back. As a result, while these variogram types are useful for confirming the ranges of continuity on the lag axis, they should not be used to determine the variability on the $\gamma(h)$ axis.

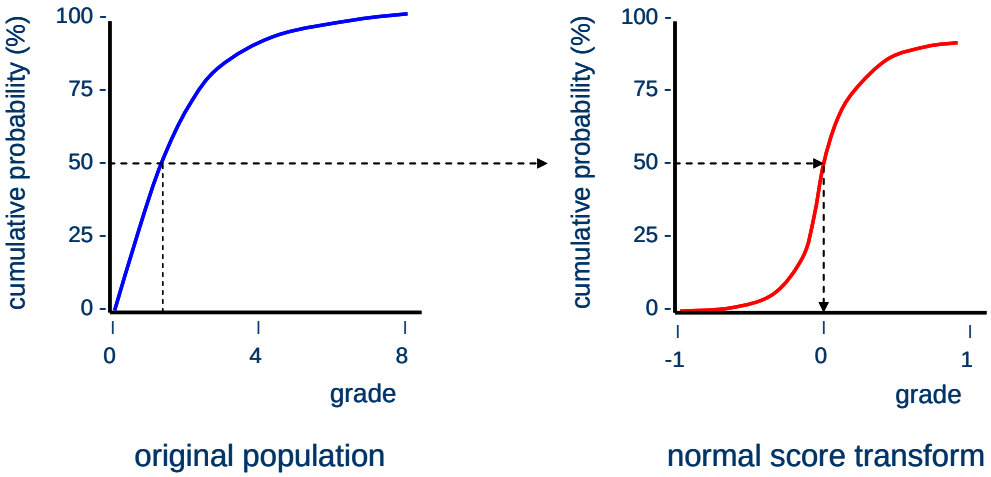
The following sections expand on the normal scores, indicator and pairwise relative variograms.

Normal scores variograms

Data transformation

For normal scores variograms the data is transformed before variogram calculation. The normal scores transform is a direct mapping of the original sample data to a known normal or Gaussian distribution with a mean of zero and a variance of one (Figure 3.60).

Figure 3.60 Normal score transformation process

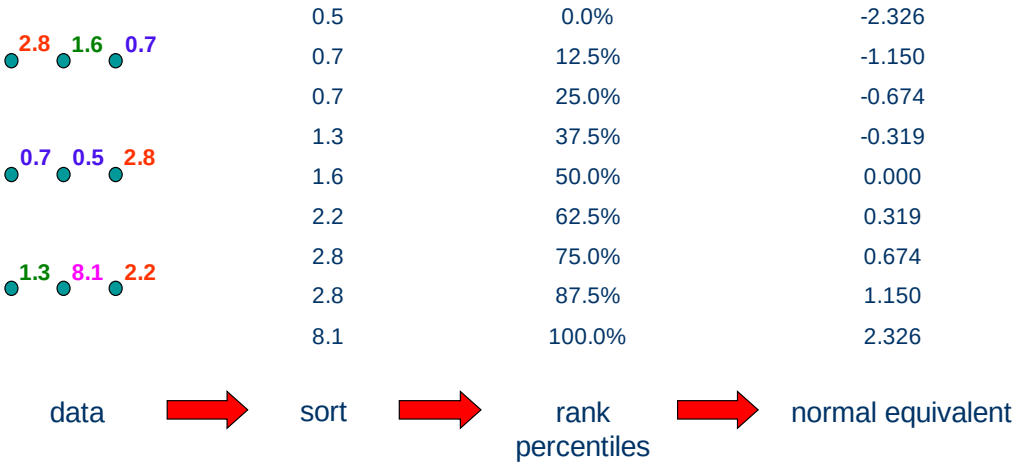


Normal scores transformed values can be calculated by:

- Sorting the sample data in ascending order.
- Calculating the percentiles for the rank of each sample.
- Calculating the corresponding normal data value on a normal distribution (use Excel's "=NORMSINV(percentile)")

Figure 3.61 shows an example of the normal score transform using the nine samples illustrated.

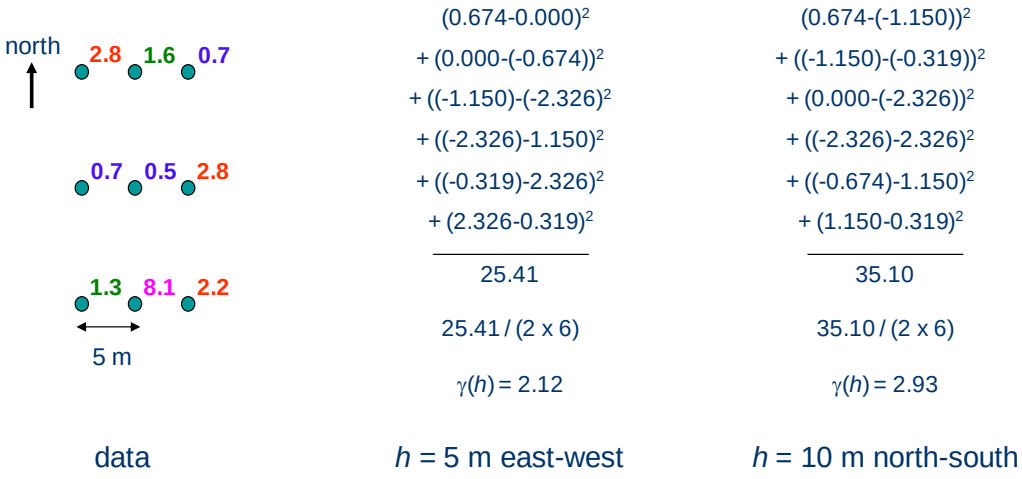
Figure 3.61 Worked example - normal score transformation



Variogram calculation

Once the normal scores transform has been carried out, the variogram calculation is carried out as per the traditional variogram but using the transformed values. Figure 3.62 shows the variogram calculations for the example above using a 5 m east-west lag and a 10 m north-south lag.

Figure 3.62 Worked example - normal score variogram calculation

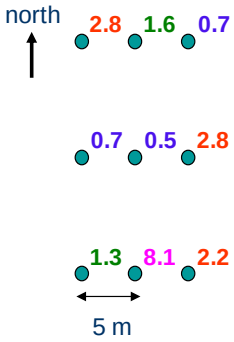


Pairwise relative variograms

A pairwise relative variogram reduces the effect of extreme grades by dividing each sample pair by the average of the paired values squared. If there is a high value, then the average will also be high, thus reducing the significance of the pair on the overall average.

Figure 3.63 shows the variogram calculations for the nine sample example using a 5 m east-west lag and a 10 m north-south lag.

Figure 3.63 Worked example – pairwise relative variogram calculations



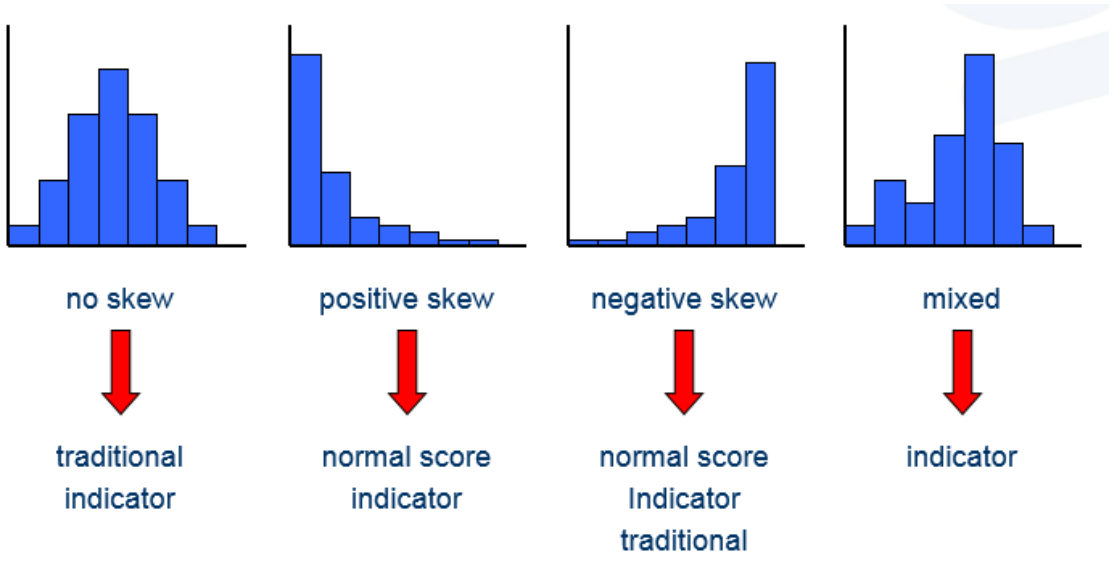
data	h = 5 m east-west	h = 10 m north-south
	$(2.8-1.6)^2/((2.8+1.6)/2)^2$	$(2.8-0.7)^2/((2.8+0.7)/2)^2$
	$+ (1.6-0.7)^2/((1.6+0.7)/2)^2$	$+ (0.7-1.3)^2/((0.7+1.3)/2)^2$
	$+ (0.7-0.5)^2/((0.7+0.5)/2)^2$	$+ (1.6-0.5)^2/((1.6+0.5)/2)^2$
	$+ (0.5-2.8)^2/((0.5+2.8)/2)^2$	$+ (0.5-8.1)^2/((0.5+8.1)/2)^2$
	$+ (1.3-8.1)^2/((1.3+8.1)/2)^2$	$+ (0.7-2.8)^2/((0.7+2.8)/2)^2$
	$+ (8.1-2.2)^2/((8.1+2.2)/2)^2$	$+ (2.8-2.2)^2/((2.8+2.2)/2)^2$
	6.370	7.519
	6.370 / (2 x 6)	7.519 (2 x 6)
	$\gamma(h) = 0.53$	$\gamma(h) = 0.63$

3.5.3 Selecting a variogram type

Selection of an appropriate variogram type is dependant on the statistical distribution of the sample data within the domain of interest. A summary of the main variogram types and the distributions they work best with is included below. Figure 3.64 summarises this information graphically.

- Traditional:
  - Sensitive to extreme grades but works well for distributions with little or no skew. Also used for negatively skewed data distributions.
- Normal scores:
  - Reduces the impact of extreme outliers and has a robust back-transformation. Most effective for positively skewed distributions but can also be applied to negatively skewed distributions.
  - Is required for sequential gaussian simulation which uses the raw, not back-transformed, normal scores variogram.
- Indicator:
  - Is the only method which does not assume a single grade population within a domain. Indicator variograms can be used where you have spatially integrated populations and domains with variable grade behaviour according to grade ranges.
  - Can be applied to any data distribution.
- Pairwise relative:
  - Can be used to verify the ranges of continuity. Is useful for domains containing a limited number of samples.

Figure 3.64 Selecting a variogram type



3.5.4 Parameters and tolerances for variogram calculations

There are several parameters that can be adjusted during variogram calculation:

- Lag distance:
  - Separation distance for sample pair selection (Figure 3.65). A good starting point is to look at a lag spacing equivalent to or slightly longer than your average drillhole spacing. Several lags should be assessed to determine which provides the best structured variogram. Lags of less than your drillhole spacing should not be used.
- Number of lags:
  - How many lags are calculated? For example for a 10 m lag if 5 are calculated then variograms will be calculated for lags of 10, 20, 30, 40 and 50 m.
- Lag tolerance:
  - Samples are rarely spaced at exact distances apart. A tolerance is applied to the lag distance so that sample pairs will be selected if they lie within the lag distance +/- the tolerance. Generally the lag tolerance is set at half of the lag spacing so that no samples are missed. For example for a lag spacing of 10 m the tolerance would be 5 m and sample pairs are selected for distances of 5 to 15 m, 15 to 25 m and so forth. An additional variogram calculation will be carried out for any pairs within the first half lag (0 to 5 m) (Figure 3.65).
- Tolerance angle:
  - Samples are rarely located in the optimal directions from each other. When calculating directional variograms a tolerance angle can be set to control the sample pairs which are selected (Figure 3.66). Tolerance angles need to be narrow enough to allow for any anisotropy (varying ranges of continuity dependant on direction) to be defined, while at the same time maintaining sufficient sample mass to give stable variograms for interpretation. Note to calculate an omni-directional variogram, a tolerance angle of 90º is used to select all sample pairs.

- Band width:
  - When using tolerance angles, the width expands continuously meaning that with increasing lag distance you are also increasing the selection area for sample pairs. This is controlled using the band width which is the width at which the selection area stops expanding and proceeds in a straight line (Figure 3.66).

Figure 3.65 Lag distance and lag tolerance

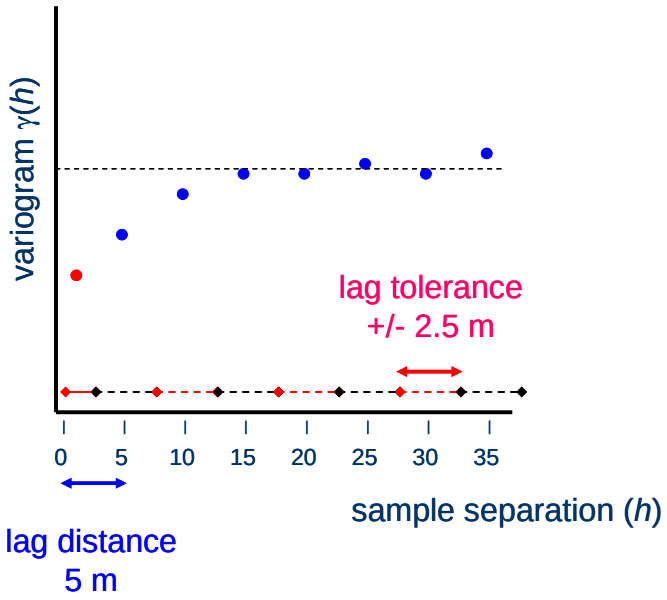
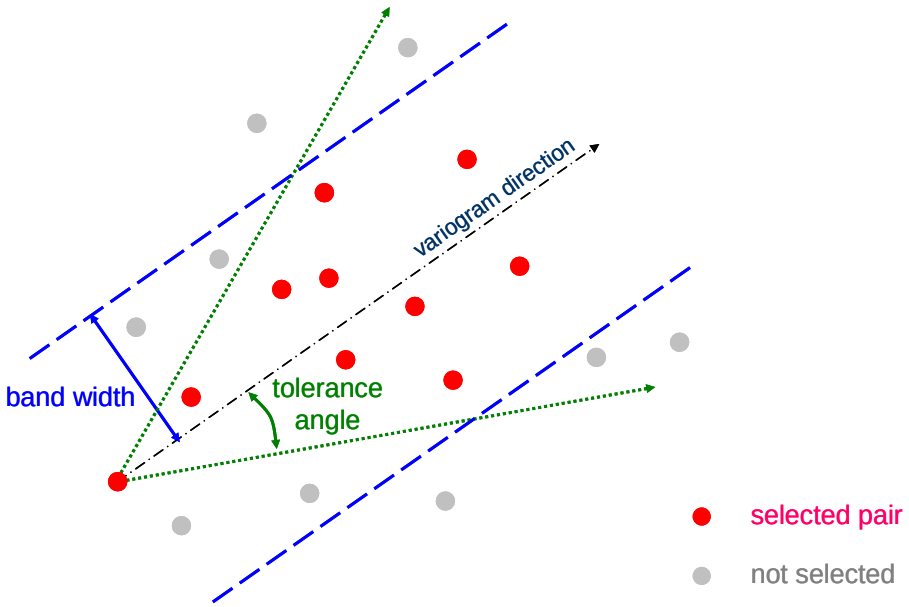


Figure 3.66 Tolerance angle and band width

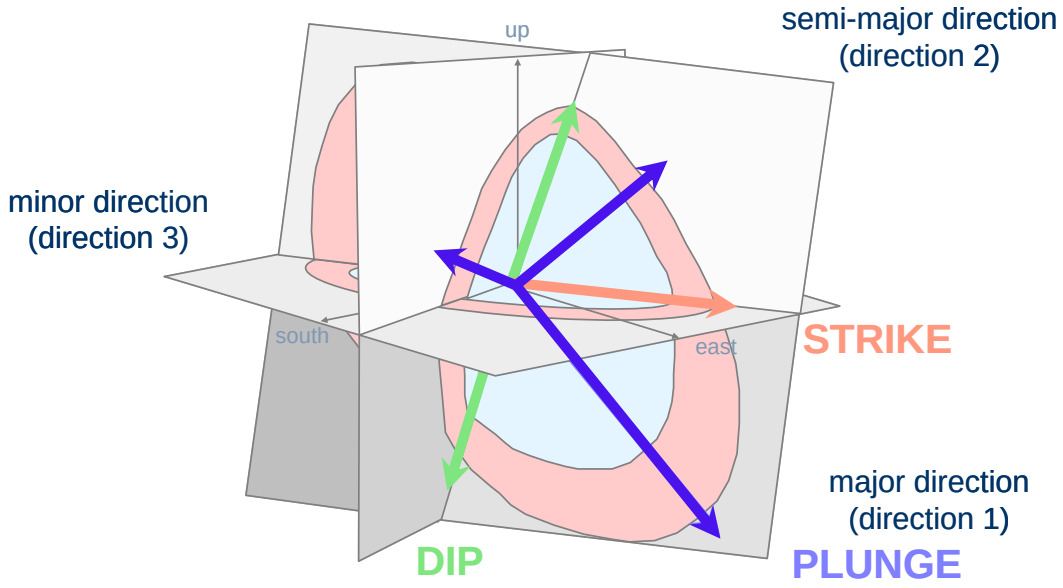


3.5.5 Directional analysis

In order to use a variogram for estimation, variograms need to be modelled in the three orthogonal directions to define a three dimensional ellipsoid. This allows variogram values to be calculated by the estimation software for any separation distance in any orientation.

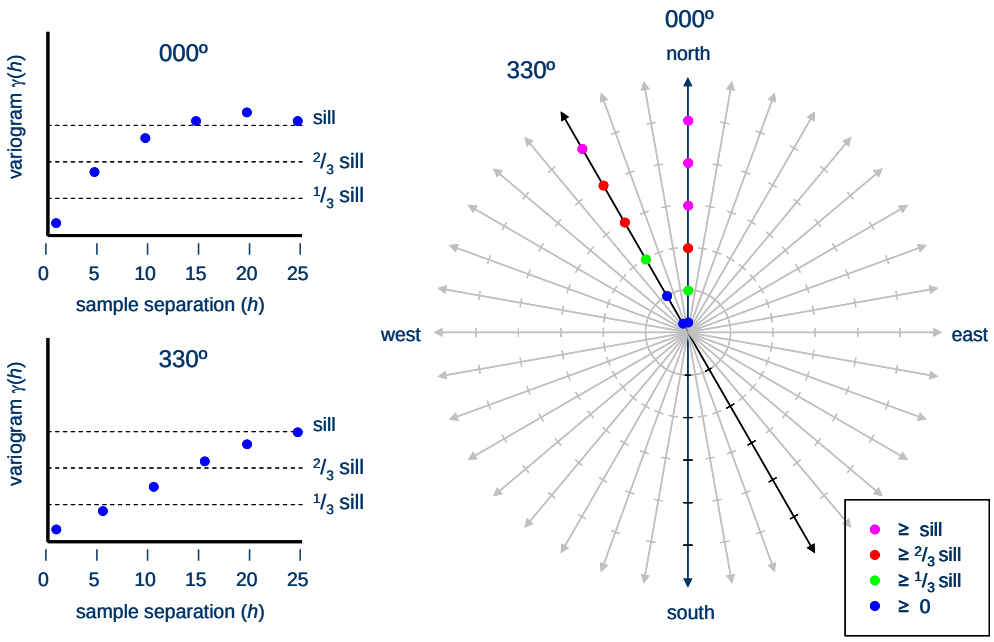
If there is no anisotropy in the domain and the ranges of continuity are the same in all directions, then an omni-directional variogram can be calculated and the models in the three directions will be the same (isotropic). If there is some anisotropy in the domain then directional variograms need to be calculated in the directions of greatest continuity, least continuity within the dip plane and perpendicular to them (least continuity). These directions are called the major (direction 1), semi-major (direction 2 or intermediate) and minor (direction 3) axes (Figure 3.67).

Figure 3.67 Orthogonal directions for variogram modelling



Geological knowledge is the best guide to defining your directions of continuity. Variogram maps or fans are a useful tool to confirming these directions or defining them if there is insufficient geological information. Instead of viewing the actual variograms, the variogram values can be plotted on a plane according to the direction and separation distance (Figure 3.68).

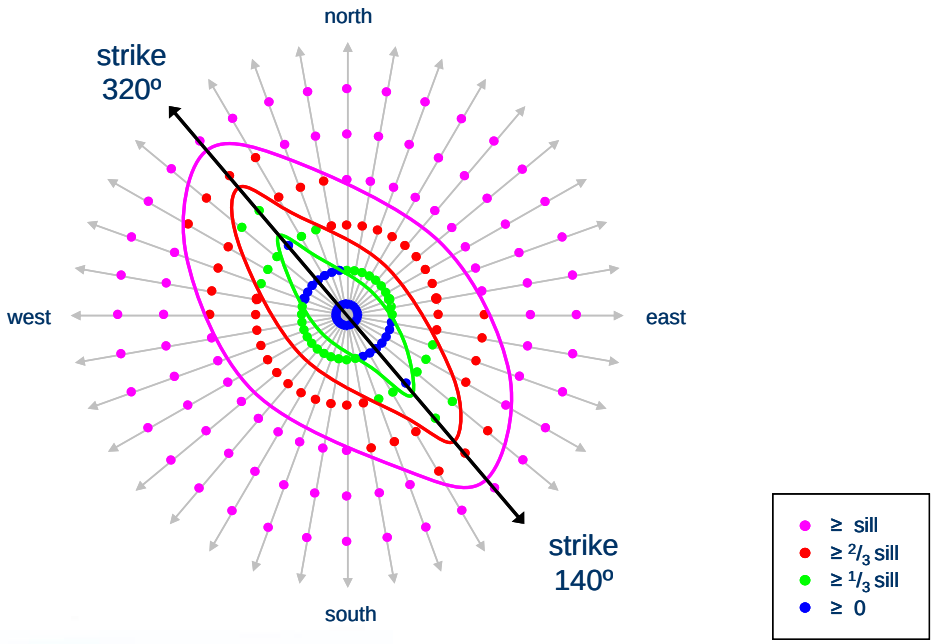
Figure 3.68 Variogram fans



If variograms are calculated in a suite of directions, for example at 10° horizontal increments, the values can then be contoured to summarise the spatial relationships for that plane of directions (Figure 3.69). It is useful to have one of the contours at the value of the total data variability as this indicates when the variogram reaches the sill.

The direction of maximum continuity in the plane is interpreted as the direction with the lowest variability for the longest range (i.e. greatest continuity).

Figure 3.69 Directional analysis using variogram fans

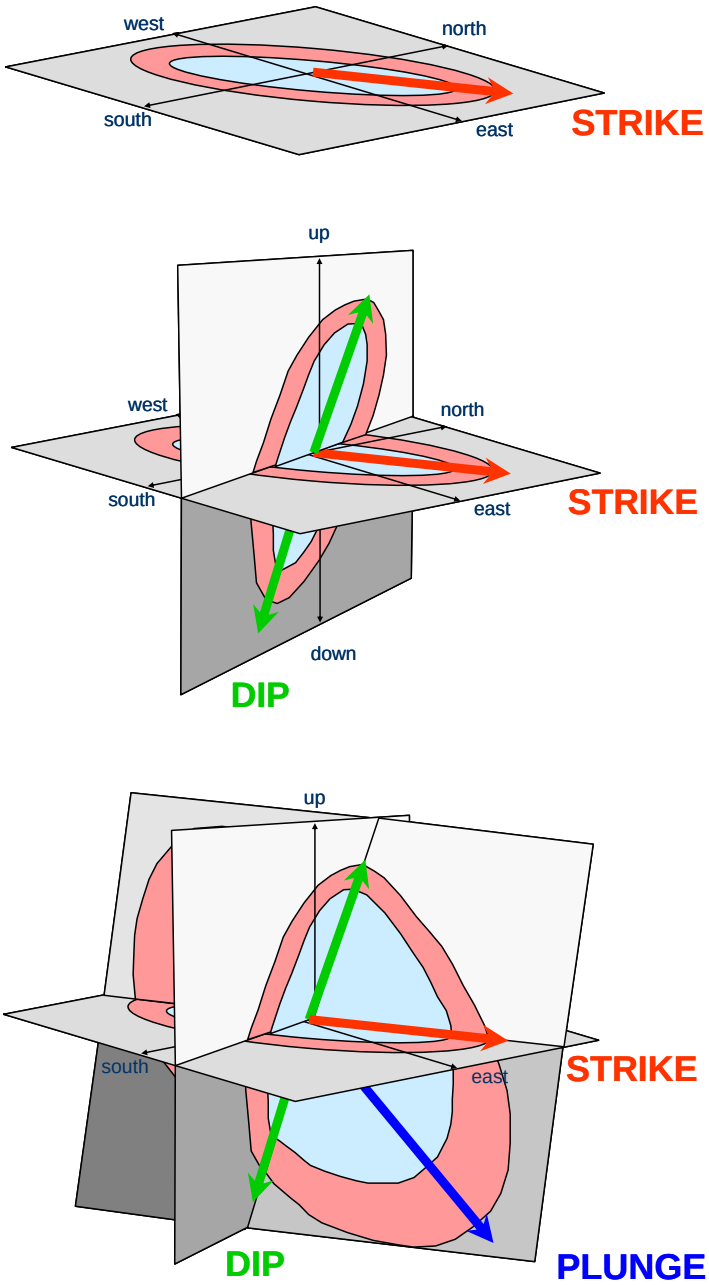


The strike of the mineralisation can be interpreted from the contours of the horizontal incremental variograms (Figure 3.70, top).

Since the dip of mineralisation is orthogonal to the strike, variograms calculated with an across strike bearing and at incremental dips can then be contoured to provide a basis for interpreting the dip of mineralisation (Figure 3.70, middle).

Once the strike and dip have been interpreted, variograms in potential plunge directions (i.e. within the dip plane) can then be calculated. The plunge of mineralisation is the direction of greatest mineralisation continuity within the dip plane (Figure 3.70, bottom).

Figure 3.70 Directional analysis using fans to interpret strike



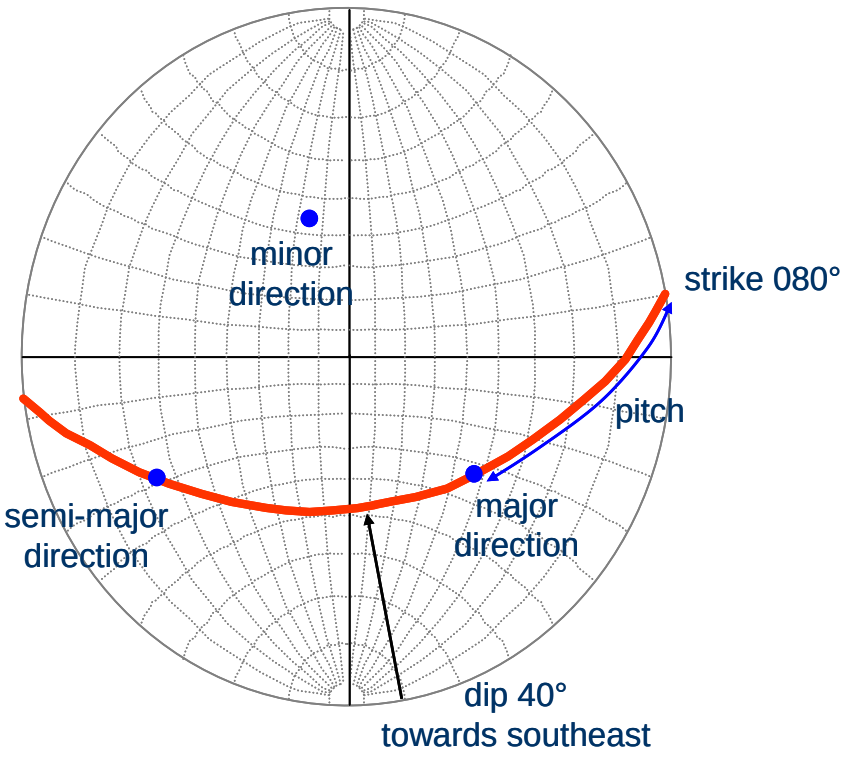
Once the strike, dip and plunge of the mineralisation are defined, these can be used to define the major, semi-major and minor directions for variogram modelling as shown previously in Figure 3.67.

Where there is a plunge to the mineralisation, this direction will be the major direction. If there is no plunge to the mineralisation, then the major direction will either be the strike or the dip direction, depending on which has greater continuity.

Confirming directions using stereonets

The directional analysis can be checked using a stereonet (Figure 3.71). The major and semi-major directions should plot on the same great circle; with the minor direction as the corresponding pole.

Figure 3.71 Directional analysis using a stereonet



3.5.6 Interpreting and modelling variograms

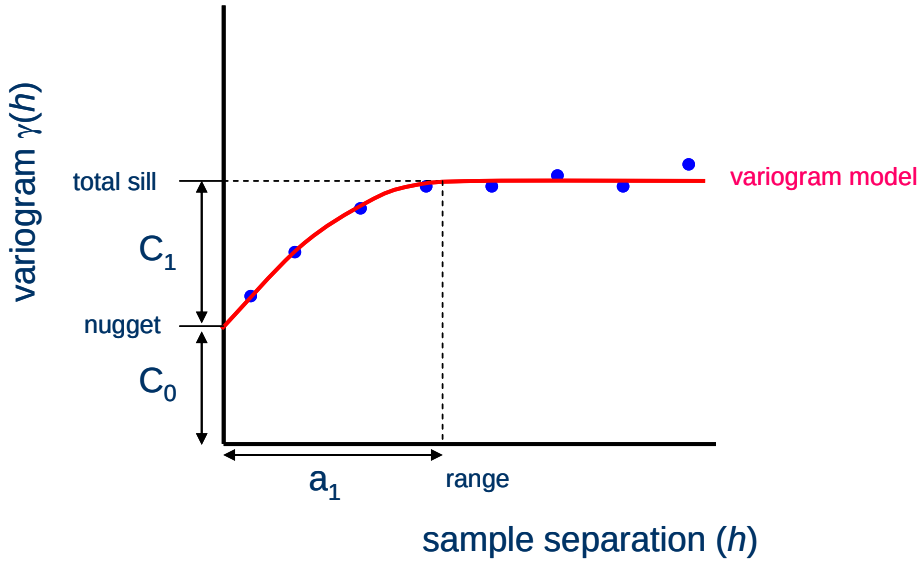
Once the three orthogonal directions have been determined, then the variograms need to be interpreted and a best fit mathematical model fitted to each direction.

Figure 3.72 highlights the major features of a variogram model, some of which have been introduced previously.

- The **nugget effect** or nugget describes the expected difference between samples when the separation distance is almost negligible. The nugget effect encompasses both the inherent small scale variability (precision) and any errors due to the sampling process (incorrect and correct errors). The nugget is often written as C_0.
- The **total sill** represents the total variability inherent in the data. The sill is equivalent to the total data variance that would be calculated using the variance statistic. It is the total variability irrespective of spatial orientation between samples. The sill is often written as C_1; however be careful with this as C_1 refers to the sill component (difference between the nugget and the total sill) rather than the total sill value.

- The **range** of continuity is the lag or separation distance at which the variability reaches the sill. When samples are separated by distances beyond the range of continuity they have no spatial correlation. Samples separated by distances less than the range of influence are spatially correlated. The range is often written as a_1.

Figure 3.72 Variogram model features



Model types

The shape of the variability between the nugget effect and the total sill is controlled by the type of variogram model we choose to model the variability with.

There are three common or standard model types available in most software packages (Figure 3.73).

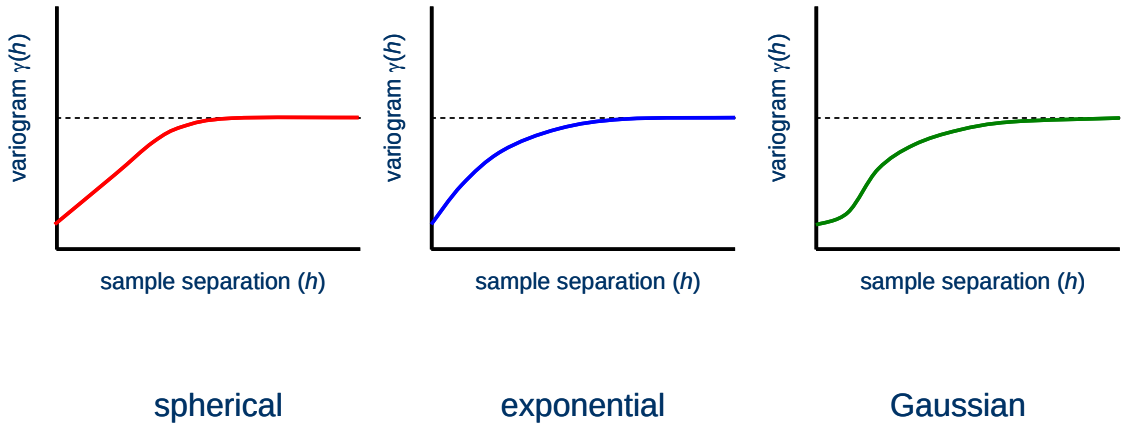
- Spherical model.
- Exponential model.
- Gaussian model.

The spherical model is linear for short separation distances and then curves into the sill near the range of influence.

The exponential model curves from zero separation distance until it levels off near the range of influence.

The Gaussian model has a flat almost nugget like contribution for short distances, before it curves towards the sill in much the same way as the exponential model. This model suggests a degree of smoothing has occurred at short distances and should alert the analyst to investigate the data more closely (for example downhole smearing or split compositing).

Figure 3.73 Variogram model types



Nested variogram models

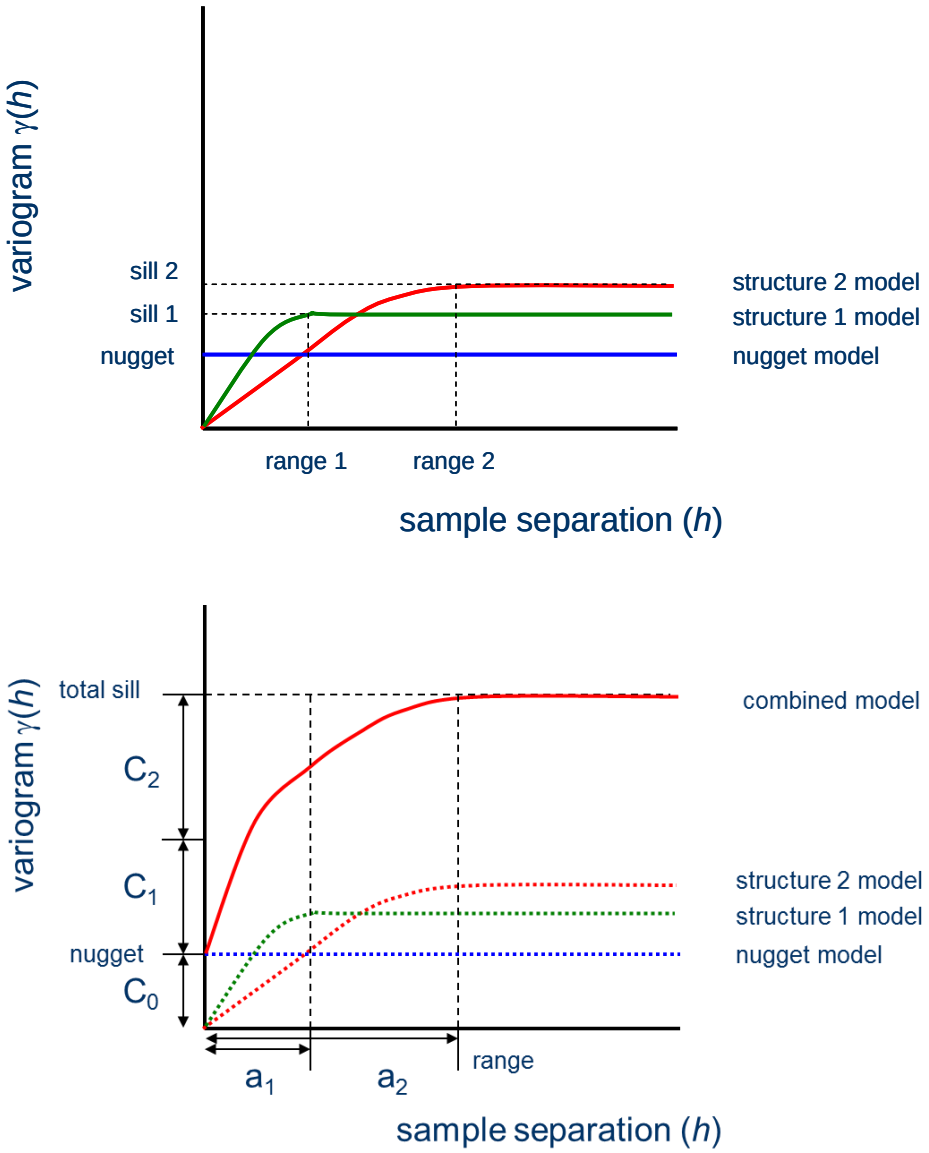
Real variograms typically appear more complex than the standard variogram model shapes discussed above. However, the standard variogram model shapes can be added together to create more complex looking variogram models (Figure 3.74). This is called variogram nesting and is accomplished simply by adding several standard variogram model shapes on top of each other.

In reality the standard models looked at previously are made up of two nested models as they contain a nugget model which is a straight line, added to one of the standard models.

When using nested variogram models, each model is referred to as defining a structure. For example the first model is the nugget model and defines the nugget effect; if another two models are used then they are said to define the first and second structures.

When more than one structure is modelled, the sill and range values are referred to as the sill of structure one (C_1) and the sill of structure two (C_2). In the same way the ranges are referred to as the range of structure one (a_1) and the range of structure two (a_2). The total sill would then be the nugget (C_0) + the sill of structure one (C_1) + the sill of structure two (C_2).

Figure 3.74 Nested variogram models showing three individual models (top) and the combined model (bottom)



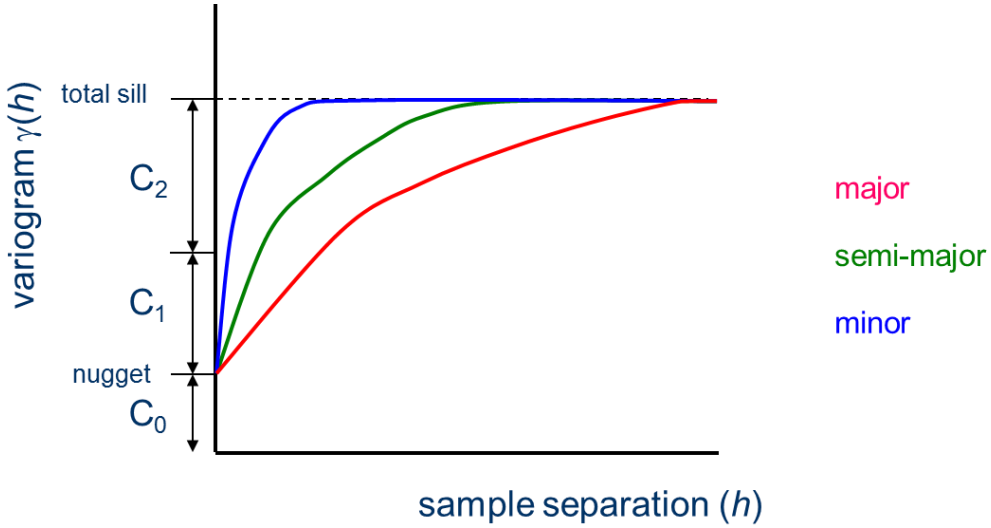
Interpreting variograms

When interpreting variograms there are some rules which should be followed. Because one three dimensional model is being defined, it is important that the models in the three orthogonal directions all have the same nugget effect and the same sill values. This also means that there must be the same number of nested structures and same model types used. The ranges however, can be different for each of the directions.

There are different ways of achieving these objectives. One way is presented here:

1. Use the direction with the closest spaced data (usually the downhole direction), calculated with small lag increments, to interpret the nugget effect. This is discussed further in the following section.
2. Apply this nugget effect to the three orthogonal directions.
3. Model the three variograms interactively until a reasonable fit is achieved for all (Figure 3.75).

Figure 3.75 Variogram models for three orthogonal directions



Modelling the nugget effect

Interpreting the nugget effect is the first step in defining a variogram model. As the nugget effect defines the variability at very short distances, the orthogonal variograms may not provide the best information for interpretation due to the sample spacing in these directions.

Nugget effects are usually modelled or interpreted using the closest spaced data available. For mining situations the closest spaced data is typically in the downhole direction where samples are adjacent. In this instance the sample spacing is equivalent to the composite length and hence a very small lag can be used to give an indication of the behaviour of the variability at short distances.

Downhole variograms can be defined by using the drillhole identifier as a key for the sample pair collection (i.e. sample pairs must both be sourced from the same drillhole) or by calculating a directional variogram in the direction of the main drilling orientation.

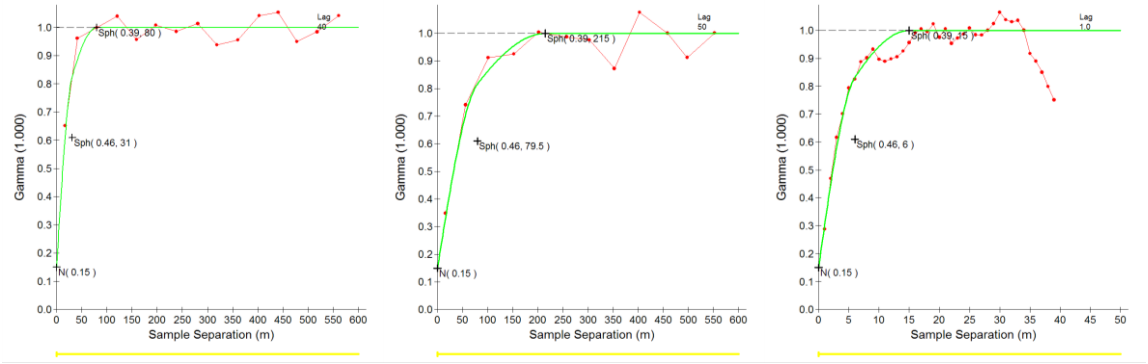
If working with narrow domains then the downhole variogram is probably not suitable as there will be a very limited amount of data downhole. In this instance an omni-directional variogram can be used (90º tolerance) as an alternative.

The main area of interest when modelling the nugget effect is the first few points near the axis. It is good practice to zoom in on this area and try and get a good fit to these initial points.

Always keep an eye on the number of sample pairs used to calculate each point. The first point on a variogram is often based on a lot less pairs and hence there is less confidence associated with this value.

Figure 3.76 shows a case study where the downhole variogram indicates a lower nugget than would be modelled if the major or semi-major directional variogram were used.

Figure 3.76 Case study showing variogram models for major, semi-major and downhole directions



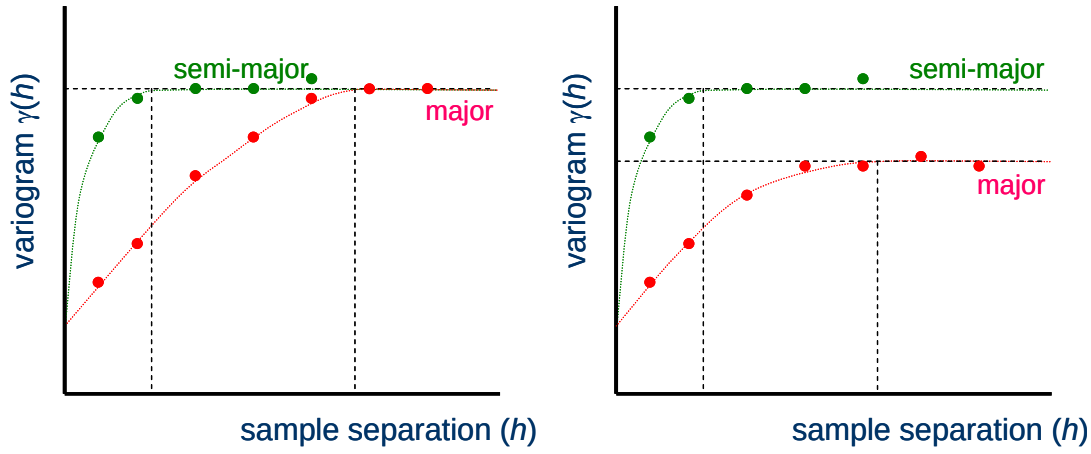
major direction semi-major direction downhole

Modelling zonal anisotropy

When modelling three directional variograms, there may be different ranges of continuity in each direction but these typically level out at the same total sill in all directions. This change in continuity is called **geometric anisotropy** (Figure 3.77, left).

There are instances where the total sill appears to be different in different directions. This is called **zonal anisotropy** and indicates that the variance of the data is not consistent throughout the domain but varies dependant on direction (Figure 3.77, right). The variograms in the different directions may also have different ranges of continuity. Strictly speaking, if this is occurring then the domain is not stationary as the variance should be consistent.

Figure 3.77 Geometric and zonal anisotropy



geometric anisotropy zonal anisotropy

Figure 3.78 shows two examples of where zonal anisotrophy can occur.

In practice zonal variograms are modelled in the same way as geometric variograms, using the highest sill for all directions and applying an additional structure with an extreme range in the directions with a lower sill to model them up to the higher sill (Figure 3.79).

Figure 3.80 illustrates a case study where the major direction shows a much lower apparent sill than the semi-major direction. In this instance, a long range structure of 10,000 m has been added to the major direction to model the variogram up to the total sill.

During estimation, the search ellipse defined to indicate which samples to use for estimation should be restricted to the real ranges of continuity, and the additional extreme range ignored.

Figure 3.78 Zonal anisotropy examples

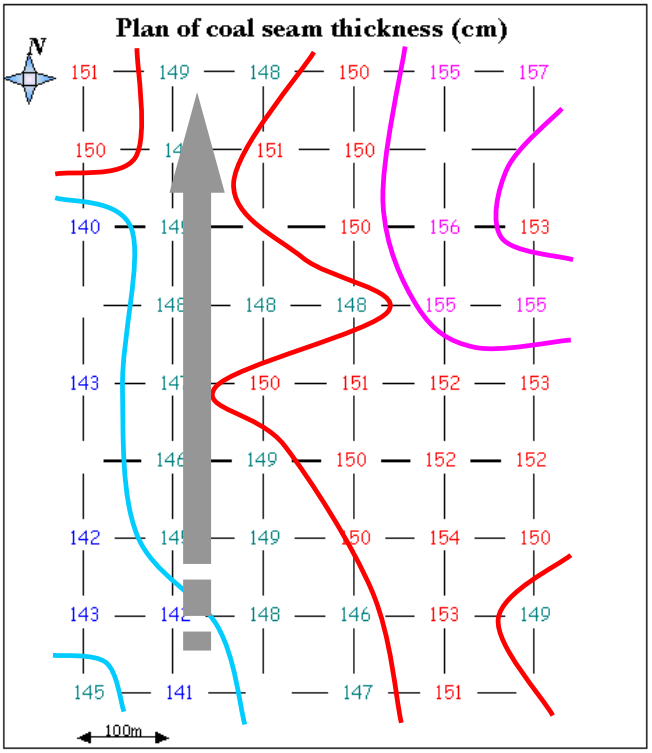


Figure 3.79 Modelling zonal anisotropy

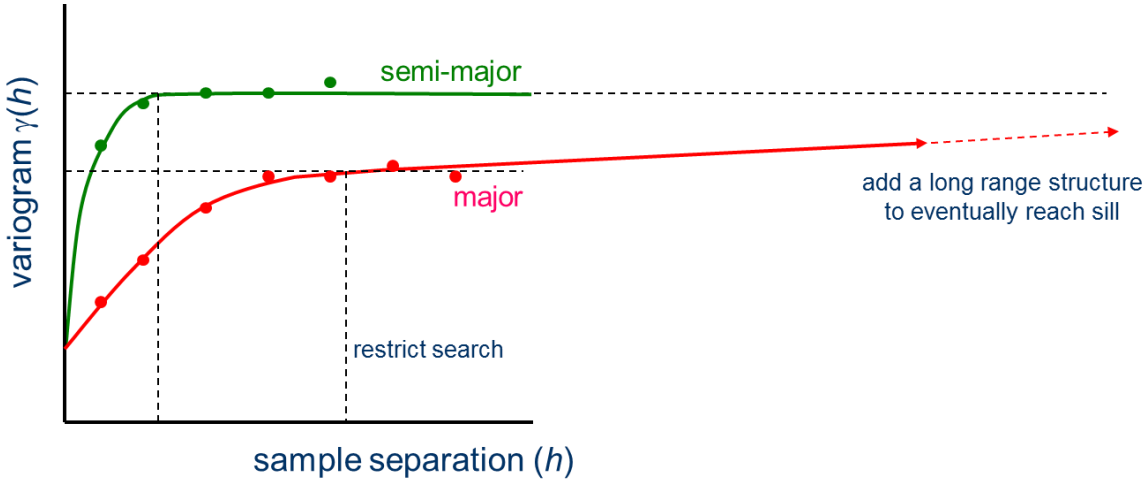
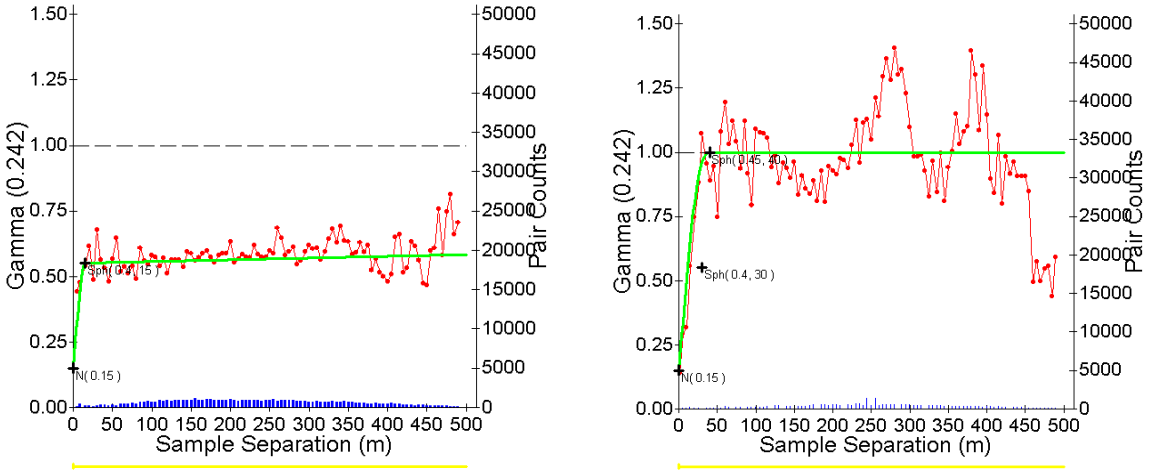


Figure 3.80 Case study showing zonal anisotropy



Modelling hole effects

Hole effects are due to “banding” in the mineralisation and where there are repeated zones of mineralisation and waste. This banding manifests itself in the variogram as waves where the peaks indicate the distances of maximum difference and troughs indicate the separation distance for repeated similarity (Figure 3.81 and Figure 3.82). If hole effects are occurring, the first thing to do is review the domaining to determine whether sub-dividing the domain will remove this effect.

To model a hole effect variogram, focus on the first repetition of the variogram and model up to the sill, ignoring the subsequent repetitions. The search ellipse for sample selection during estimation should be limited to the range of continuity seen in the first repetition (Figure 3.83, left). This method assumes that the continuity will be similar within each band.

The use of an inappropriate lag can disguise a hole effect as, for example, the sample pairs may all come from within the mineralised bands. This can result is an incorrect long range continuity being modelled (Figure 3.83, right).

Figure 3.81 Hole effects

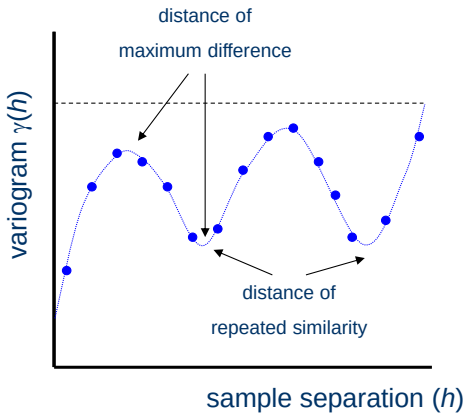
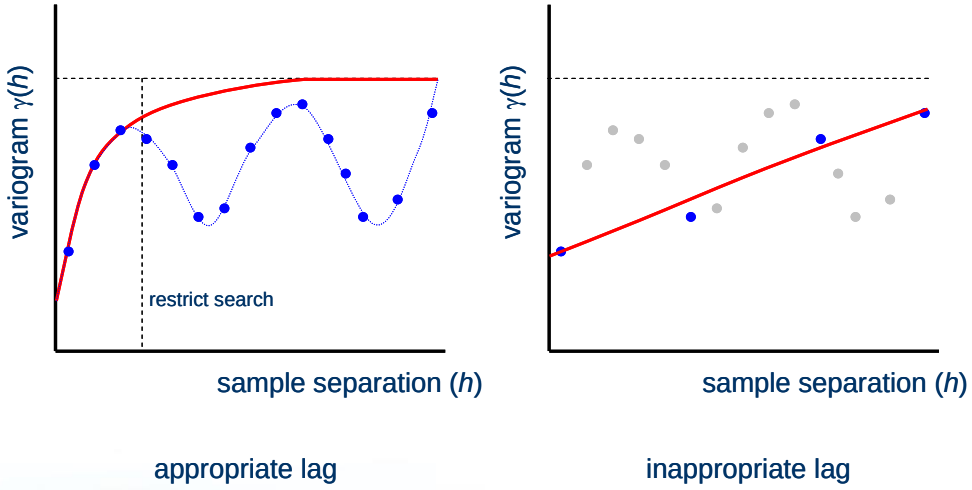


Figure 3.82 Hole effect example

Figure 3.83 Modelling hole effects



appropriate lag inappropriate lag

Modelling trends

Trends in the variogram occur when, instead of the variogram levelling out at the sill, the difference between the sample pairs continually increases as the separation distance increases (Figure 3.84). This effect is the result of a grade trend within the domain, whereby the mean grade of the domain gradually changes from low to high within the domain. This is common in strataform deposits such as mineral sands or PGEs (Figure 3.85).

As with hole effects and zonal anisotropy, if there are trends in your data then the domain is not strictly stationary. The first option should always be to investigate whether sub-domaining will remove the trend.

If sub-domaining is not an option either due to lack of data or the consistency of the trend, then the recommendation is to model the variogram up to the sill, ignoring the points above the total sill (Figure 3.85).

Figure 3.84 Trends

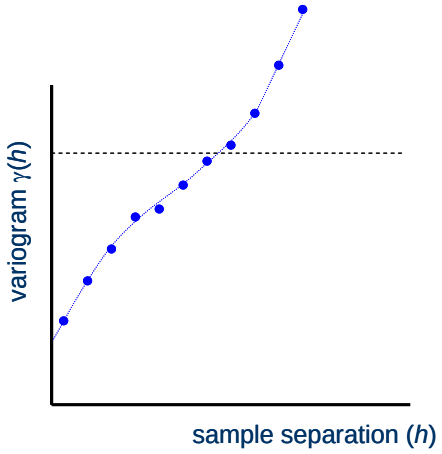


Figure 3.85 Trend example

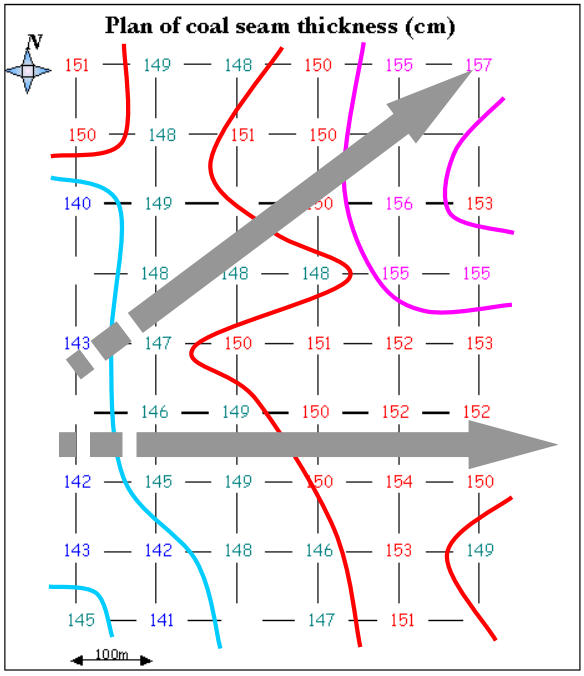
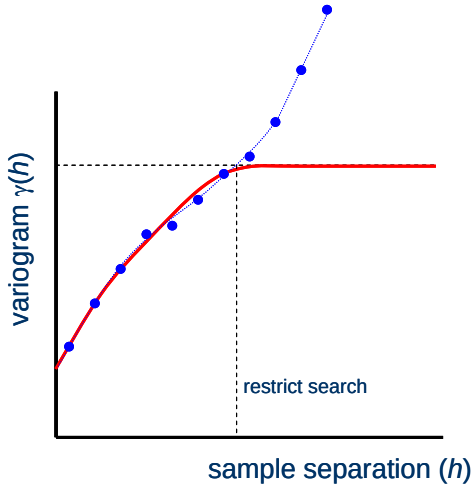


Figure 3.86 Modelling trends



Back-transformation

If normal scores or log variograms are modelled, a back-transformation process must be carried out to adjust the nugget and sill proportions to match the true data variance.

Generally the nugget will increase and the first sill value will proportionally increase giving steeper short range variability.

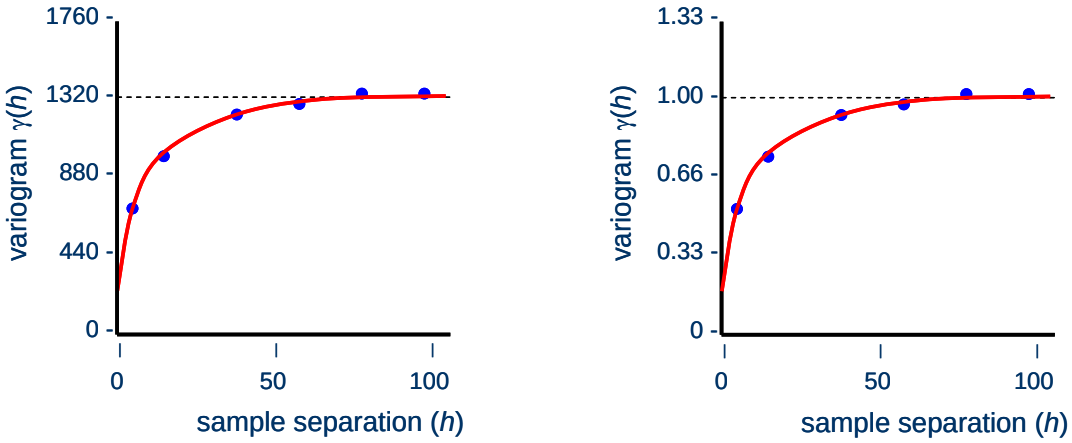
3.5.7 Standardising variogram models

With variograms the total sill is equivalent to the total data variance. When working with large numbers the proportion of the total variability associated with each structure may not be immediately evident. For example a nugget effect of 280 could be any proportion of the total variability dependant on the sill. Even if the sill is known to be 1,320 then it is not always immediately evident that a nugget effect of 280 is 21% of the variability.

A common practice to make variograms easier to read is to standardise the variogram so that the total sill is 1 (Figure 3.87). This means that a 21% nugget will always have a variogram value of 0.21. This practice also makes it easier to compare variogram models for different domains and/or attributes as they will all have the same total sill.

In order to standardise a variogram, all values are divided by the total data variance to scale them to 1. This process does not impact on the estimation process and is purely designed to make the variograms easier to read.

Figure 3.87 Standardising variogram models



original variogram
total sill = 1320

standardised variogram
total sill = 1

4 Resource estimation

There are several geostatistical concepts that need to be introduced prior to discussing grade estimation. These concepts provide the background information for selecting an appropriate block size and input parameters for estimation.

Once appropriate parameters have been selected, grade estimation can be carried out. The resultant estimate can then be validated to ensure that it is representative of the input data and classified to describe the risk inherent in the estimate.

4.1 Concepts

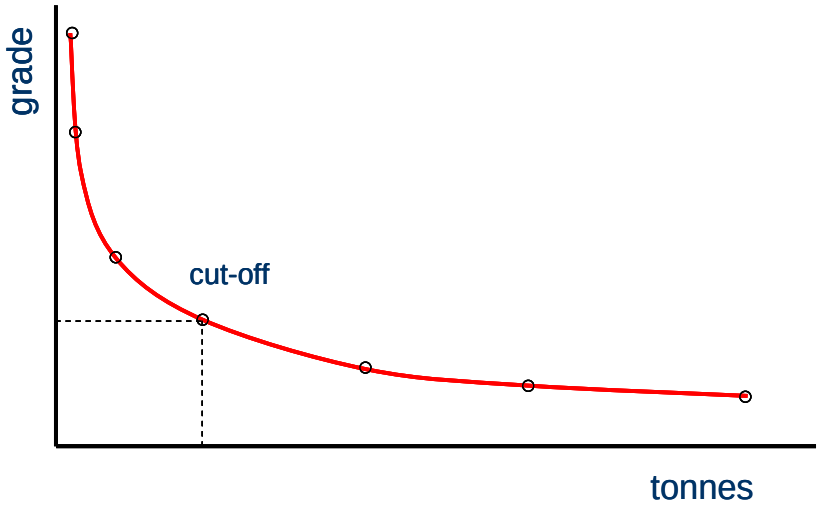
4.1.1 Grade tonnage curves

Grade tonnage curves provide a summary of the estimated resource. Grade tonnage curves are generated by determining the following for each grade cut-off in a series of cut-offs:

- Identify all blocks greater than or equal to the grade cut-off.
- Accumulate the tonnes of those blocks.
- Density weight the block grades to calculate an average grade for those blocks.

The grades and tonnes for the series of cut-offs can be plotted to create a grade tonnage curve (Figure 4.1). Grade tonnage curves can be used to compare estimates from different models or different phases (for example exploration versus grade control).

Figure 4.1 Grade tonnage curve



4.1.3 The volume variance effect

The volume variance effect describes the decreasing variance associated with increasing support or volume. It can also be described in terms of the increase in grade dilution that occurs as the volume of the mining unit increases.

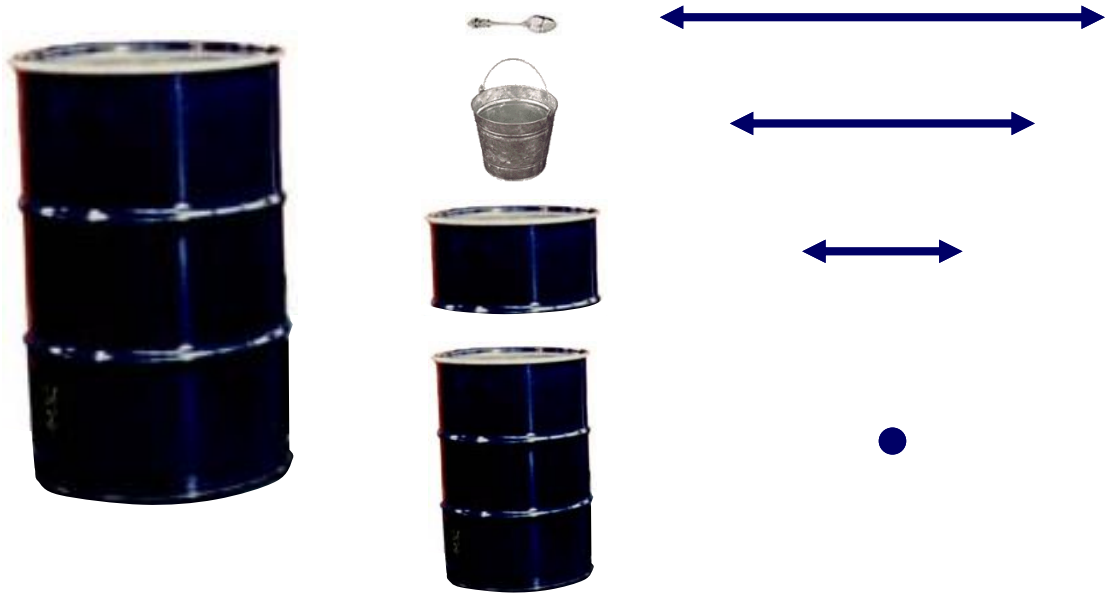
The volume of the mining unit is termed the selective mining unit or SMU and is a function of mining method, equipment, geometry of the mineralisation and the grade variability within the mineralised domains.

Consider a coarse gold environment where the total deposit is represented by a 44 gallon drum (Figure 4.2). If this deposit is mined with teaspoons, some of those teaspoons will contain pure nuggets of gold and some will be totally barren. This will result in a very wide range of potential grades presented by the teaspoons.

Consider mining exactly the same deposit with beach buckets. Each bucket may contain some grade, but it is extremely unlikely there will be a beach bucket full of nuggets. The surrounding barren material dilutes the high grade nuggets. Similarly it is unlikely that a beach bucket will be totally barren. So the range of grades from the beach buckets is less than the range of grade from the teaspoons.

The greater the volume used for selection, the greater the dilution of grades at both the high and low grade extremes. This decrease in the range (or variance) of grades with increasing volume is known as the volume variance effect.

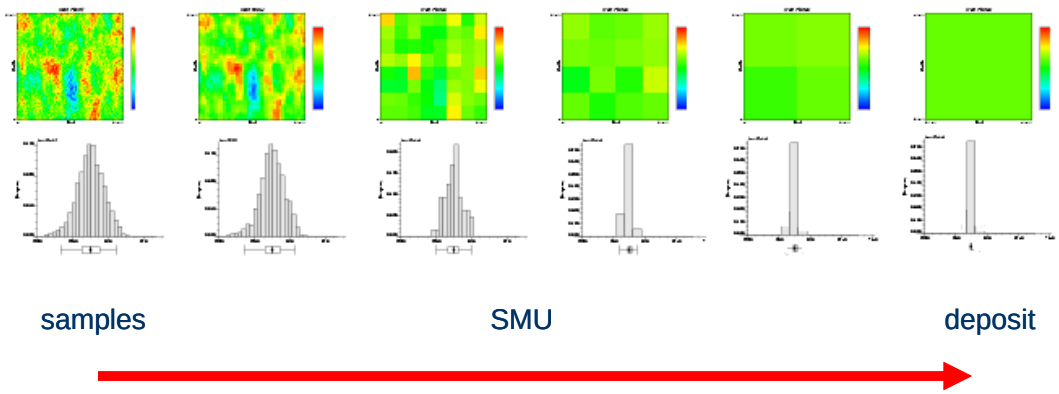
Figure 4.2 The volume variance effect



4.1.4 The volume variance effect and block size

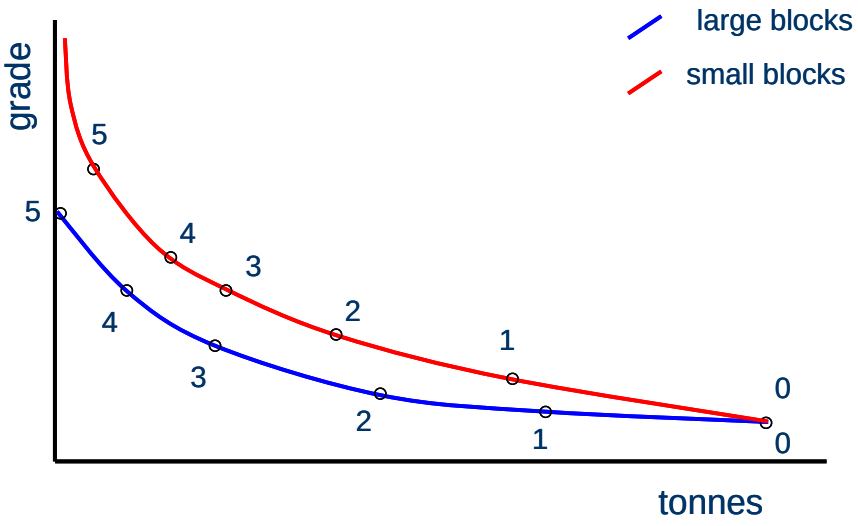
The volume variance effect can also be illustrated by looking at the change in the shape of a histogram of grade data with increasing volume or block size. This is illustrated by the case study in Figure 4.3. As the blocks are progressively averaged into larger blocks, the variability in the blocks decreases and the histogram becomes narrower.

Figure 4.3 Case study illustrating block size and the volume variance effect



This change in block size and histogram shape also results in a change in the grade tonnage relationship when reporting above a cut-off (Figure 4.4). For cut-offs below the mean grade a smaller, more selective block size will report less tonnes at a higher grade. If the cut-off is higher than the mean grade then the smaller blocks can report more tonnes at a higher grade.

Figure 4.4 Grade tonnage curves with change in block size



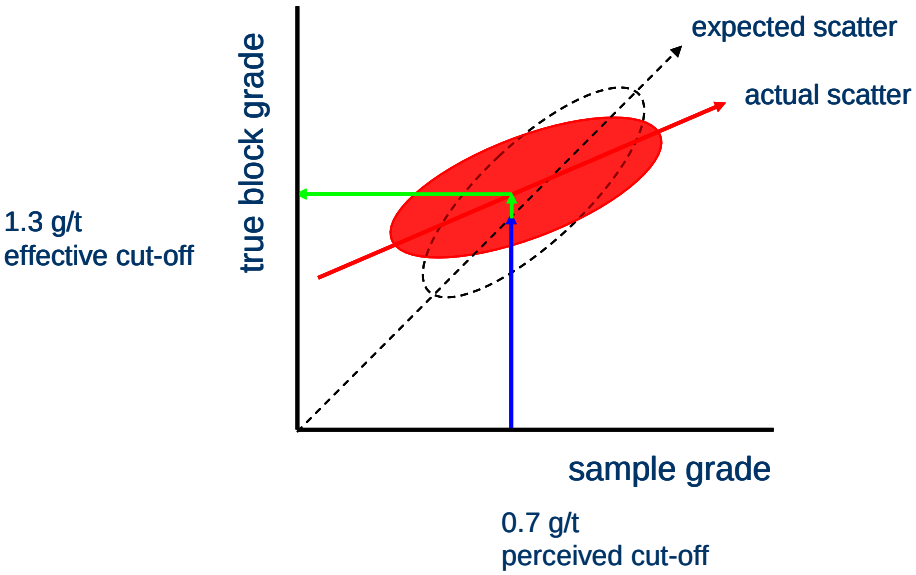
The problem now is which block size gives the correct grade tonnage relationship? This depends on what level of selectivity is actually going to be achieved during mining.

4.1.5 The volume variance effect and selectivity

Ignoring the volume variance effect is equivalent to assuming selectivity at the scale of sampling. If during mining, grade control is carried out using a polygonal method (for example defining ore/waste boundaries based on blasthole grades) then this is not taking into account the volume variance effect and will result in incorrect ore/waste definition unless the mining method can match the sampling level of selectivity.

As mining cut-offs are generally less than the mean grade of the domain, using samples to define ore/waste boundaries equates to applying a higher than expected cut-off grade resulting in ore being sent to the waste dump (Figure 4.5).

Figure 4.5 The effect of the volume variance effect on selectivity



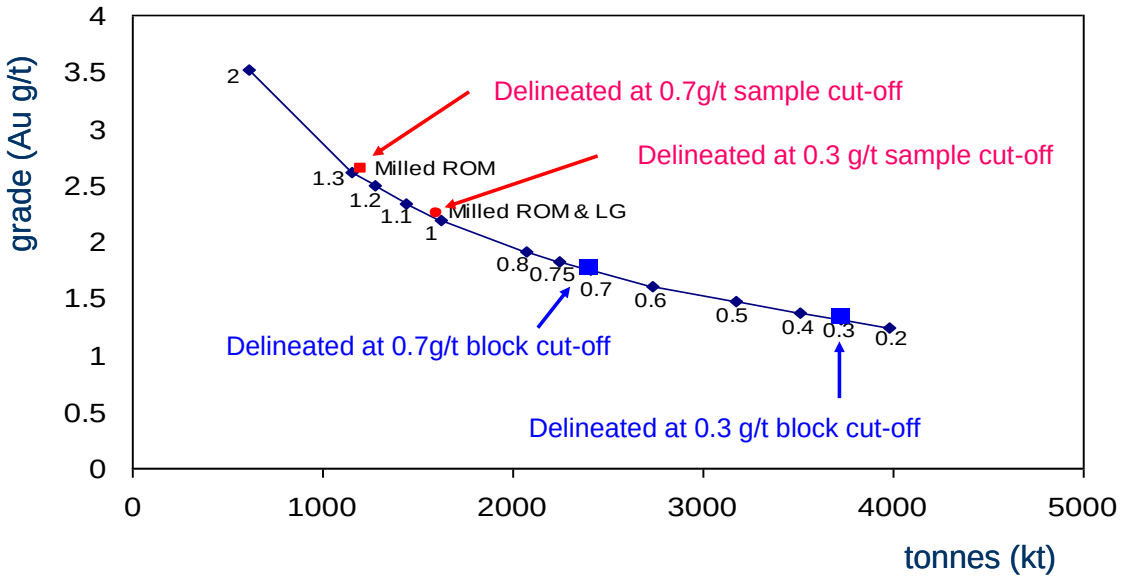
Case Study – volume variance effect and selectivity

The McKinnons case study is an interesting example of the volume variance effect on selectivity. A discrepancy was noted between the resource estimate and grade control at the 0.3 g/t and 0.7 g/t gold cut-offs used to define low grade stockpile material and high grade mill feed material (milled ROM).

The grade control process delineated ore by digitising polygons around the grade control data at the 0.3 g/t and 0.7 g/t gold cut-offs. The top cut sample grades within the polygons were averaged to provide a grade estimate for the mill feed and low grade stockpile material.

The actual result was less tonnes were being milled and stockpiled than predicted by the resource estimate and higher grades were being achieved. The resource estimate, grade control estimate and actual results are illustrated on the following grade tonnage curve (Figure 4.6).

Figure 4.6 Grade tonnage curves for the McKinnons case study



This is a classic case of the grade control process not taking account of the volume variance effect.

The use of the polygonal method for delineating the ore resulted in a higher effective cut-off being applied. The effective cut-off grades applied were 1.0 g/t and 1.3 g/t gold instead of 0.3 g/t and 0.7 g/t respectively. The selectivity graph shown previously illustrates this effect for the mill feed cut-off (Figure 4.5).

The net effect of delineating the ore without accounting for volume variance was that more than half of the ore was misclassified as waste and the low grade stockpile was in fact above the mill feed cut-off.

This issue is often realised only when the low grade stockpiles are milled and higher grades than expected are obtained.

4.1.6 Variance

There are several different types of variance that need to be understood with respect to the volume variance effect and the resource estimation process.

Point variance

The total variability within a domain is estimated by calculating the variance of the sample grades within the domain. This total variance is also referred to as point variance.

Block variance

Block variance is simply the variance between block grades as opposed to sample grades. With increasing block size, the variability between the block grades decreases as a result of the volume variance effect.

Dispersion variance

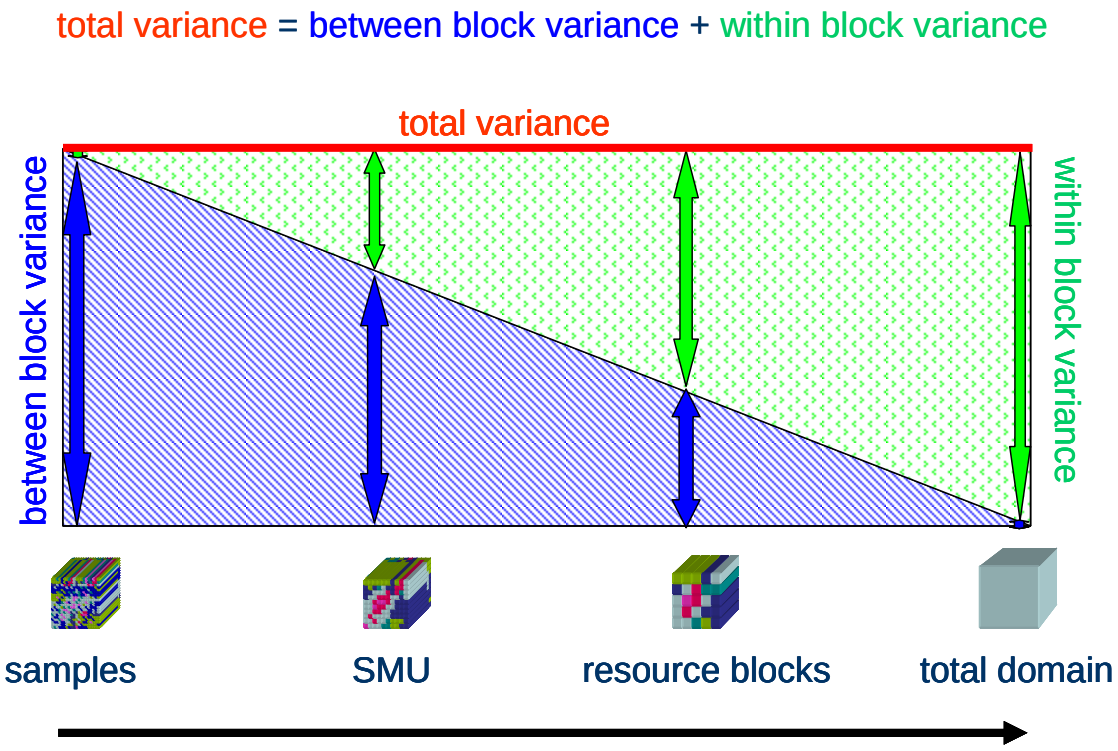
Variability is never destroyed or removed from a system, it is instead dispersed. As the variance decreases with increasing block size, the remainder of the variability is absorbed into the blocks.

The total variability can be broken down into the variability between the blocks and the variability absorbed into the blocks. This is referred to as dispersion variance and can be written as:

total variance = between block variance + within block variance

With increasing block size, the between block variance decreases and the within block variance increases. This concept is illustrated in Figure 4.7.

Figure 4.7 Dispersion variance



The within block variance can be calculated from the variogram by most mining software (for any block size) and is often referred to as the geostatistical f-factor.

Given that the total variance is represented by the point variance (or variogram sill), the anticipated variability between blocks (for any block size) can be estimated using the above equation, rewritten as:

between block variance = total variance – within block variance

or,

between block variance = total sill – f-factor

Kriging variance

Kriging variance is very different to the other variances discussed. It is a by-product from the kriging system, which provides a relative measure of confidence in each block estimate with respect to data coverage.

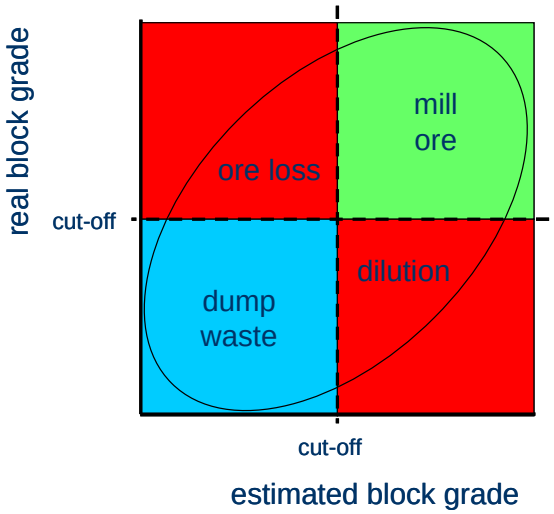
Kriging variance is a relative measure of error only as at no stage are grades taken into account in the calculation. This is discussed further in Section 4.4.5.

4.1.7 Misclassification

Misclassification is the incorrect assignment of ore and waste. Not understanding or taking into account the volume variance effect can result in misclassification. In addition, poor estimation quality will result in misclassification. There are four possible outcomes when a block of material is mined (Figure 4.8):

- Ore: the block is estimated to be above cut-off and it really is above cut-off
- Waste: the block is estimated to be below cut-off and it really is below cut-off
- Dilution: the block is estimated to be above cut-off and it really is below cut-off
- Ore loss: the block is estimated to be below cut-off and it really is above cut-off

Figure 4.8 Misclassification



Reality is accurately forecasted for the first two scenarios. However, the third and fourth scenarios present problems in that waste is milled or ore is discarded. Both of these scenarios cause financial losses. Consequences of incorrect prediction include:

- In the long term:
  - Incorrect pit optimisation or location of development.
  - Incorrect design and sizing of mining and processing facilities.
- In the medium term:
  - Scheduling and cash-flow forecasting difficulties.
  - Increased cost per tonne of ore.
- In the short term:
  - Misallocation of ore and waste material.

The critical objective of the resource estimation process is to minimise the estimation error, thereby minimising misclassification.

4.2 Building the block model

4.2.1 Block size selection

Selecting an appropriate block size is extremely important for achieving accurate estimation and minimising misclassification.

The optimal block size for estimation is mainly a function of drillhole spacing. A rule of thumb is one half of the drillhole spacing or larger. If the deposit has consistent mineralisation and a low nugget, a quarter of the drillhole spacing may be acceptable.

Block models tend to be generated using block sizes which are larger than the anticipated mining selectivity (SMU). Change of support is the process of adjusting the block model estimates so that the results reflect the expected grade tonnage relationship at the anticipated SMU. This is discussed in Section 0.

There are a number of other practical factors to take into account, including:

- What is the geometry of the mineralisation and drilling with? It is a good idea to use anisotropy in keeping with these when defining the block sizes for testing. For example, if the drill grid has an anisotropy of 1:2 (e.g. 10 m by 20 m), use block sizes with the same anisotropy.
- What block size is required to get reasonable volume resolution? This is mainly an issue in narrow vein style deposits.

Statistical optimisation can also be carried out to quantify the effectiveness of the estimation process at a variety of block sizes. This can provide a useful aid to block size selection; however, it should always be tempered with reality and practical considerations. The theory and method for carrying out this statistical optimisation are detailed in Section 4.5.

4.2.2 Block coding

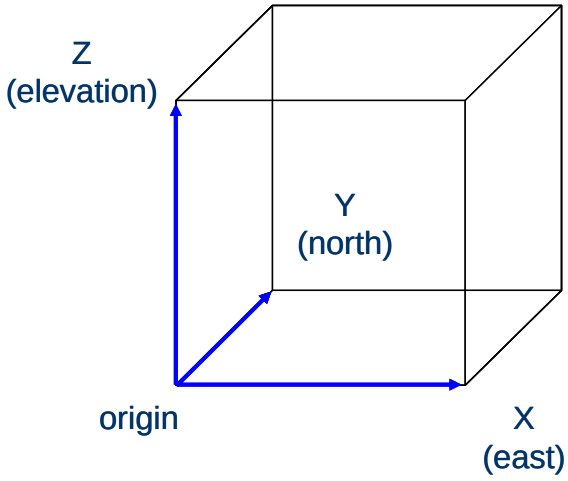
Once an appropriate block size has been selected, the next step is to build the block model. At this stage the block model is usually referred to as a volume model as it defines the estimation domain volumes but contains no grade information.

It is important to setup the volume model so that it covers the total area of interest. For example, the mine design process may require an expanded area around the mineralisation to allow for pit walls and/or dilution.

Most mining software packages work with block model prototypes where the user defines the origin, extent and block size. Commonly the origin is defined as the bottom left (west) corner of the volume model (Figure 4.9); however, this does vary in some mining software packages.

When defining the origin, it is good practice to set it up so that the drillhole lines are centred on the blocks rather than between blocks.

Figure 4.9 Block model prototype definition



Once the prototype is defined the volume model can be coded using validated wireframes. It is important to use the same codes as were used to code the drillhole data. Consider the order of coding if there are overlapping domains.

In addition to the wireframes used for the drillhole coding, a topographic surface is commonly used to define the top of the model. If working in an active open pit, a pit survey may be used instead of topography.

Subcells can be used to help with volume resolution when coding the block model. Most mining software allows the specification of a minimum subcell size or the number of subcells to use per parent cell. When defining the degree of subcelling, think about the geometry of the domains as well as the practical mining scale (SMU).

Some ways of validating the volume model coding include:

- Visually checking that the volume model is correctly coded. Especially watch at the edges of domains.
- Comparing the volume of each domain in the volume model to the wireframe volumes.

4.3 Search neighbourhood parameters

The estimation process uses the samples within each estimation domain to estimate values into the corresponding domain in the volume model. In order to do this it is first necessary to define which samples should be selected and used for the estimation of each block (search neighbourhood).

The main search neighbourhood parameters are:

- Search ellipse orientation and ranges for selecting samples.
- Minimum and maximum number of informing samples for estimation.

Search neighbourhood parameters can be statistically optimised as discussed in Section 4.5; however it is recommended that the following practical guidelines be used to select appropriate parameters before running the optimisation to validate these parameters.

Search ellipse orientation and ranges

The orientation and anisotropy of the search ellipse should be directly related to the continuity modelled in the variograms. As with variogram modelling, the three orthogonal directions are used to define a three dimensional search ellipse.

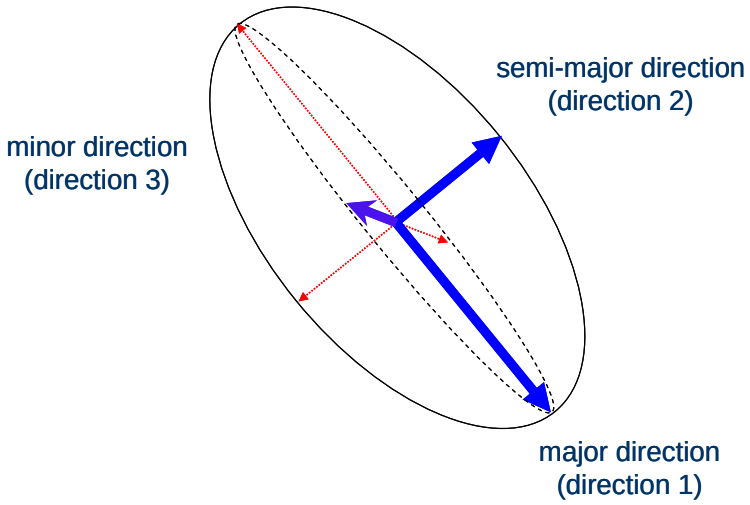
It is common practice to use the maximum ranges from the variogram models to define the size of the search ellipse ranges, as the variogram ranges indicate the distance within which there is some correlation between samples.

Always review the variograms to determine whether there are any issues which will impact on the choice of search ranges. For example, if the variogram deteriorates at 50 m but it is modelled up to the sill at 80 m, it might be more appropriate to search 50 m. Zonal anisotropy and hole effects can also impact the choice of search range as the maximum variogram range will not necessarily be appropriate in these instances (Section 3.5.6).

Note that when defining a search ellipse, the ranges are the radii of the ellipse (Figure 4.10). For example, if the variogram model indicates that there is continuity between samples to 100 m in all three directions, then a 100 m search range should be used to select samples that are within 100 m in all directions of the estimation point (200 m diameter).

Take care with domains that show a very short range continuity as these may require a larger search ellipse to ensure that sufficient samples are used for estimation.

Figure 4.10 Search ellipse radii



Minimum and maximum number of informing samples

The minimum number of samples used for estimation should only impact on the edges or sparsely drilled portions of domains, as elsewhere the maximum number of samples will be selected. Most practitioners agree that for moderate to high nugget effect domains at least ten samples should be used to produce a reliable estimate.

Selection of the maximum number of samples should consider the search ellipse and amount of samples within this area. Typical maximum number of samples per estimate is in the order of 30 to 50. Be careful as too many samples will sometimes cause over smoothing of the estimate.

Octants

Some software allows the use of octant searches. This involves sub dividing the search ellipse into eight equal sections and specifying minimum and maximum number of samples for each of these octants. A minimum number of octants can also be specified so that estimation will not take place unless a certain number of octants contain the minimum number of samples.

Dynamic search

Most software allows the use of dynamic search criteria or multiple estimation passes. This method allows for estimation using a series of passes, where the search criteria become increasingly relaxed with each pass. Typically the search ranges and number of informing samples are adjusted.

Estimation is carried out using the first search criteria; if blocks do not get estimated due to insufficient sample numbers within the search criteria then they are estimated using the second search criteria and so forth. This is a useful tool for assessing the risk in the estimate. For example, the first pass can be defined using optimised parameters which define the higher confidence estimates; the second pass can then use a reduced minimum number of samples and/or an expanded search range to define the higher risk estimates.

Key fields

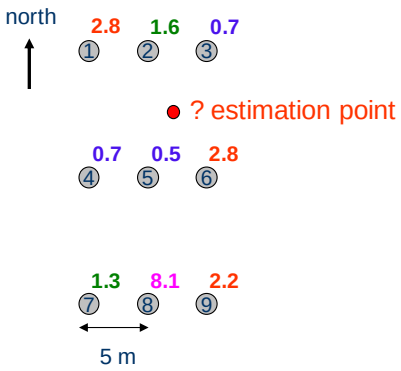
Some software allows the number of composites used for estimation to be restricted based on a key field. This is typically used to restrict the number of composites from each drillhole. The drillhole identifier is used as the key field in this instance. This method is useful to avoid the string effect which is discussed later. It is also useful in narrow undulating domains as a wider search can be used to ensure that the composites are selected, while restricting the number from each drillhole to avoid oversmoothing.

4.4 Estimation

4.4.1 Introduction

Estimation methodology has developed over time out of a need for an unbiased estimate of the grade at an unsampled point given the values of known points (Figure 4.11).

Figure 4.11 Estimation of grade at an unknown point

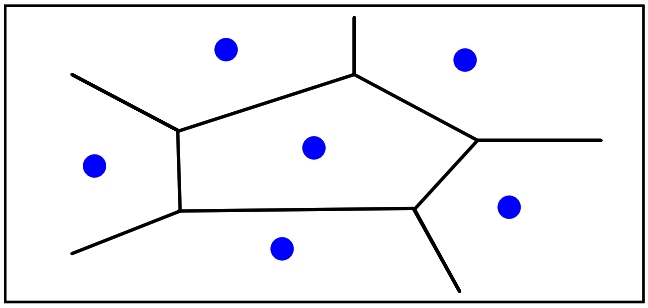


4.4.3 Polygonal estimation

In the past, traditional methods have used either a nearest neighbour or an averaging approach to assign grades to points or volumes. These methods include the following:

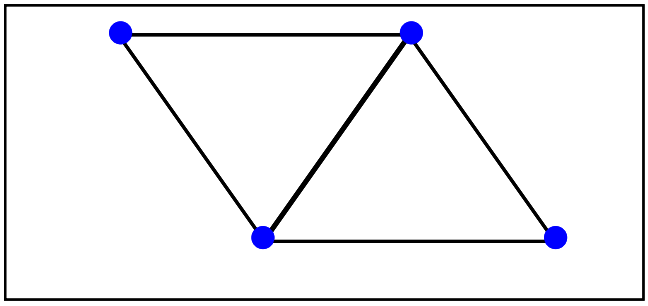
- The simplest method is to assign the value of the nearest sample to the unknown point; this is called **nearest neighbour** estimation. However, this approach under-utilises the available data and ignores any correlation between samples.
- The **polygonal method** is a nearest neighbour estimate which assigns the grade to a volume. A volume or polygon is defined around each sample point and the grade of that sample point is assigned to the polygon (Figure 4.12). This method ignores any correlation between samples and ignores the volume variance effect (larger volumes have lower variance); hence the extreme grades estimated by this method cannot be achieved during mining.

Figure 4.12 Polygonal estimation



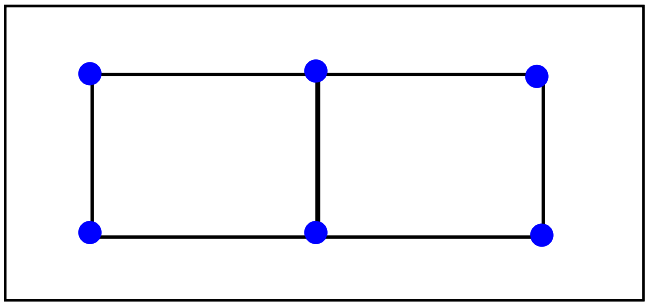
- The **triangular method** defines volumes by establishing each sample as the vertex of at least one triangle. The average of the three sample grades that form the vertices of the triangle is assigned as the grade of the triangle (Figure 4.13). While this takes some note of the volume variance effect, the correction is not uniform as the triangles have different volumes dependant on sample spacing. These estimates still tend to be more selective than reality. In addition this is a two dimensional method and does not take account of smoothing in the vertical direction.

Figure 4.13 Triangular estimation



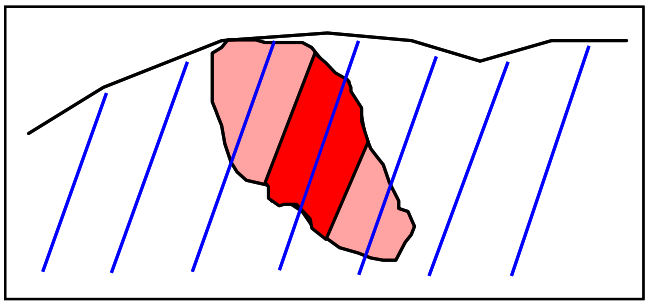
- The **quadrangular method** is an extension of the triangular method which is used when the data is sampled on a regular rectangular grid. The vertices of the rectangles are used to calculate the average grade of the rectangle (Figure 4.14). The issues raised for the triangular method also hold for the rectangular method.

Figure 4.14 Quadrangular estimation



- The **sectional method** is an extension of the polygonal method. A volume is defined around each drillhole based on half the distance to the adjacent drillholes (either side) and halfway to the adjacent sections. All samples from this drillhole that are within the interpretation are averaged and assigned to the volume surrounding the drillhole (Figure 4.15). This represents an improvement on the raw polygonal method as the extreme grades are averaged into the estimates. There is, however, no accounting for the range of influence that these samples may or may not have. In addition the volumes will be variable if the drillholes and sections are not equally spaced.

Figure 4.15 Sectional estimation



While all of the above methods and their implementation are relatively easy to understand, they typically result in an overly selective grade tonnage curve and tend to have the same or similar selectivity as the sample data. In addition they do not take into account any correlation between samples.

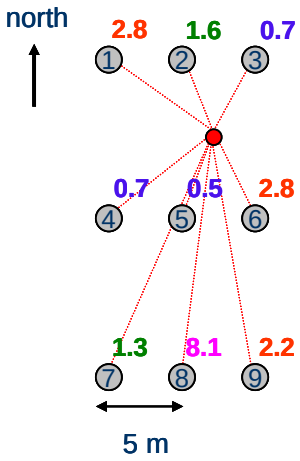
4.4.4 Inverse distance

Assuming there is some spatial correlation between the samples, it makes sense that samples closer to the unknown point are more related to it. **Inverse distance** estimation is a linear[3] technique which was developed to attempt to account for this sample to distance relationship.

Inverse distance estimation is similar to the averaging approaches looked at previously, except that each sample is assigned a weight according to the inverse of their separation distance from the point of estimation (Figure 4.16). This means that close samples receive a higher weight than samples further away.

[3] *Linear estimates are created by weighting the sample grades based on their position.*

Figure 4.16 Inverse distance estimation – samples weighted by distance



To ensure an unbiased estimate, the weights (inverse of the separation distances) are rescaled so they sum to one to ensure that the estimated grade is unbiased when compared with the sample grades. The equation for inverse distance estimation is:

$$estimate = \frac{sum\ of\ (sample\ value\ x\ inverse\ distance\ weight)}{sum\ of\ (\ inverse\ distance\ weights)}$$

where:

$$inverse\ distance\ weights = \frac{1}{(sample\ to\ estimation\ point\ distance)^{power}}$$

The inverse distance weights can also be raised to a power. This power is selected by the user in an arbitrary way. One way to think about the power parameter is to consider its effect on the estimate.

If the power is high (say about three), then the closer samples receive even more weight than the samples further away. The higher the power, the more weight is assigned to the closer samples.

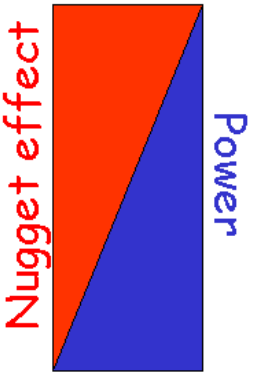
When the power is low (say one), then the closer samples still receive greater weight than the samples further away, however, their influence is reduced.

Consider the extreme case where the power is set to zero. In this instance, all inverse distances raised to zero would return a value of one. The net effect is that all samples receive an identical weight and the estimate is just an average of all samples within the search criteria.

The nugget effect from the variogram can be used as a guide to selecting the power (Figure 4.17). A low nugget effect indicates good reproducibility in the sample data. This means that samples close to an estimation point can be assumed to have a grade similar to that at the estimation point. In this instance a high power can be used so that more weight is assigned to the closer samples.

Conversely, a high nugget effect indicates poor reproducibility, and so a low power should be used so that the assigned weights are more even.

Figure 4.17 Power selection based on the nugget effect



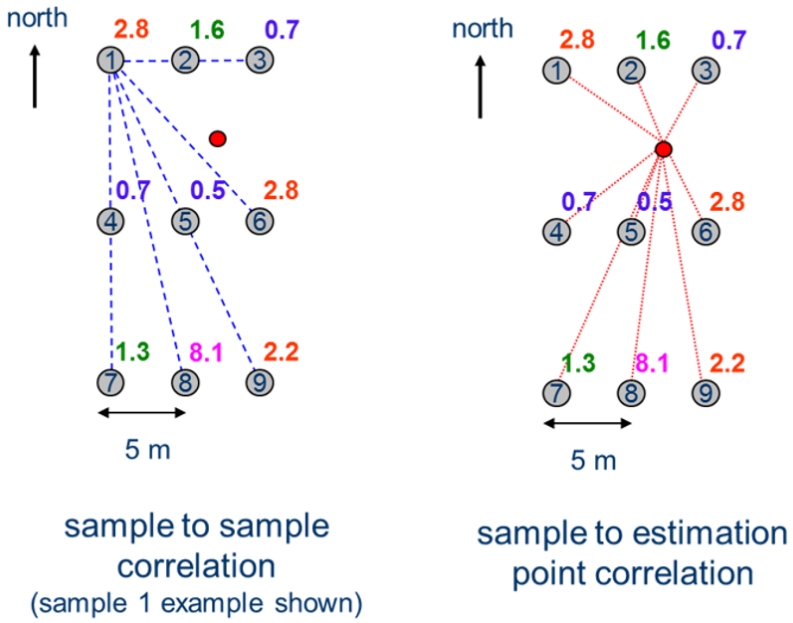
There are a number of problems with the inverse distance approach:

- Inverse distance weights are the same in all directions, they do not account for the possibility that the samples have different spatial relationships in different directions.
- The power used is arbitrary. There is no scientific explanation available for the application of different powers.
- Inverse distance estimation does not decluster the data. Clustering of the samples will bias the estimate towards the clustered grades.
- Inverse distance estimation is polygonal if there are samples close to the estimation point as, even with a low power, a very close sample will effectively receive all of the weight.

4.4.5 Ordinary kriging

Ordinary kriging is similar to inverse distance in that it applies weights to samples according to their position. The difference is that the weights are determined via the variogram model according to the samples' distance and direction from the point of estimation. This means that the weights take into account the spatial correlation between the samples, and between the samples and the point of estimation (Figure 4.18).

Figure 4.18 Ordinary kriging estimation – samples weighted by variogram



The kriging estimation equation is written as:

$$estimate = sum\ of\ (sample\ value \times kriging\ weight)$$

The following section discusses the derivation of the kriging equations.

The kriging equations

Kriging was created to serve a need; an estimation method was sought which, of all possible linear estimators, would provide an estimate that had the least overall error and would be unbiased (Best Linear Unbiased Estimator).

Consider these two criteria in detail:

- The error (variance) between the estimates and the true values must be a minimum, so the average error between the estimates and the true values must be smaller for this estimator than for any other linear estimator. This can be written as:

$$(estimate - real\ value)^2 = minimum$$

This equation can be differentiated with respect to the error (using standard calculus methods) to determine what weights are required to minimise the error.

- The estimate must be unbiased; so the sum of the weights must equal one. This can be written as:

$$(sum\ of\ weights - 1) = 0$$

- Kriging equations are used to determine optimum kriging weights for minimum variance (error) and do not use assay values but variance values calculated from variograms. This gives a set of simultaneous equations – one equation for each of the samples being used to estimate the block grade – that are solved to determine the kriging weights (λ_i). This leads to a set of kriging equations as outlined below:

*Sum of [weight (λ_i) * variance between each of the sample points (γ_{ij})] + Lagrange multiplier (μ) = variance between the block and the sample point ($\overline{\gamma}_{iV}$)*

Sum of weights (λ_i) = 1

Mathematically:

$$\sum_{j=1}^{n} \lambda_i \gamma_{ij} + \mu = \overline{\gamma}_{iV} \quad for\ i = 1,2 \dots n$$

$$\sum_{i=1}^{n} \lambda_i = 1$$

The Lagrange multiplier (μ), is needed in the kriging equations as the true variance of the deposit is not known (this can only be achieved by sampling all of the deposit!). When we have a limited sample dataset, the variance is understated compared to the true variance. This is also known as the information effect. The Lagrange Multiplier accounts for this difference.

Kriging variance

A product of the kriging system is the kriging variance, which provides a relative measure of confidence (or error) in each block estimate. Each block will have an estimate but it is naïve to think that under any circumstances that these grades will be correct to two decimal places, particularly given problems with sampling, assaying, geological interpretation, domaining and variography.

The kriging variance provides a likely range of grades (usually to two standard deviations) around the estimated grade, where the estimated grade is the most likely grade. The kriging variance is determined form the equation below:

*Kriging variance = sum of [weight (λ_i) * variance between the block and the sample point ($\overline{\gamma}_{iV}$)] + LaGrange multiplier (μ) – variability within a block $\overline{\gamma}(V)$*

Mathematically:

$$\sigma^2 = \sum_{i=1}^{n} \lambda_i \overline{\gamma}_{iV} + \mu - \overline{\gamma}(V)$$

Kriging variance does not use assay values but variance values calculated from variograms, kriging weights and the LaGrange multiplier as determined from the earlier kriging equations. Larger blocks will have more variability contained within the block compared to smaller blocks and hence a lower kriging variance. This is known as the support effect or volume variance effect.

Grade estimate

Grade estimates $Z^*(x_0)$ are calculated by summing the weights *(λ_i)* as determined from the kriging equations with the associated assay value $Z(x_i)$.

*Estimate = sum [weight (λ_i) * assay value $Z(x_i)$]*

Mathematically:

$$Z^*(x_0) = \sum_{i=1}^{n} \lambda_i \, Z(x_i)$$

The estimate is nothing more than a weighted average of samples used to determine the grade. The weights are determined by taking into consideration the nugget variance, total variance, anisotropy, ranges, the position of samples with respect to each other and the position of samples with respect to the block being estimated.

Matrices

The kriging equations can also be expressed in matrix form as shown in Figure 4.19.

Matrices are used by software to solve the kriging equations (simultaneous equations) described above. One thing that is different with matrices is the fact that covariance is used instead of variance in determining the kriging weights. This is because if variance is used, the diagonal γ(1,1) γ(2,2) ….. γ(9,9) will all be zero since the variance of a sample wth itself is zero. The zeros on this diagonal make matrix inversion slow, or even impossible, hence the use of covariance for matrices.

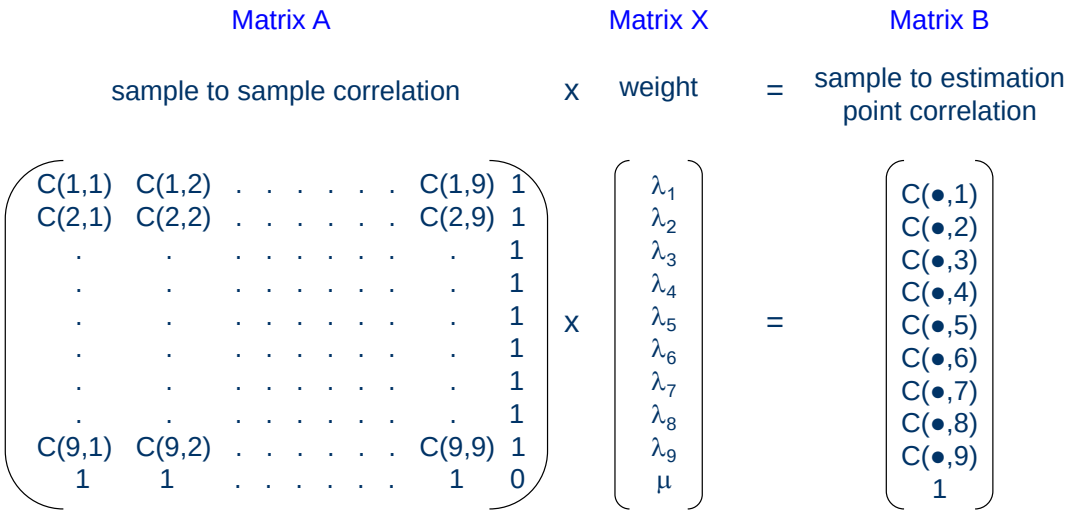
Covarince can be calculated by subtracting the estimated variance from the total variance (sill) of the variogram.

Covariance (C) = total variance (C_O + C_1) – variance ($\overline{\gamma}$)

Mathematically:

$$C = (C_O + C_1) - (\overline{\gamma})$$

Figure 4.19 Kriging system



μ= LaGrange multiplier
C = Covariance
λ= kriging weight

The kriging system that is used to derive the weights can be summarised in three matrices; Matrix A, X and B where:

- Matrix A summarises the covariance values between all the samples used for the estimation. Matrix A takes care of the declustering in the system by ensuring that lower weights are assigned in areas of clustering.
- Matrix X is the matrix of weights the system is attempting to estimate.
- Matrix B is the matrix of covariance values between the samples and the point to be estimated.

Since Matrix A and B are derived from the variogram model that is supplied to the kriging system, all that remains is to solve the kriging system to derive the weights.

Matrix A and B are known (from the variogram) and we need to work out what X needs to be to satisfy the equation. This is done using standard matrix algebra. The weights so derived are then applied to the sample values to estimate a grade for the unsampled location as previously describes.

Note the last row of matrix A contain ones (except the very last entry which is a zero) this is the unbiased condition that the sum of weights equals one (last entry matrix B). The last column of matrix A is ones (except the very last entry which is a zero) this is for the LaGrange multiplier.

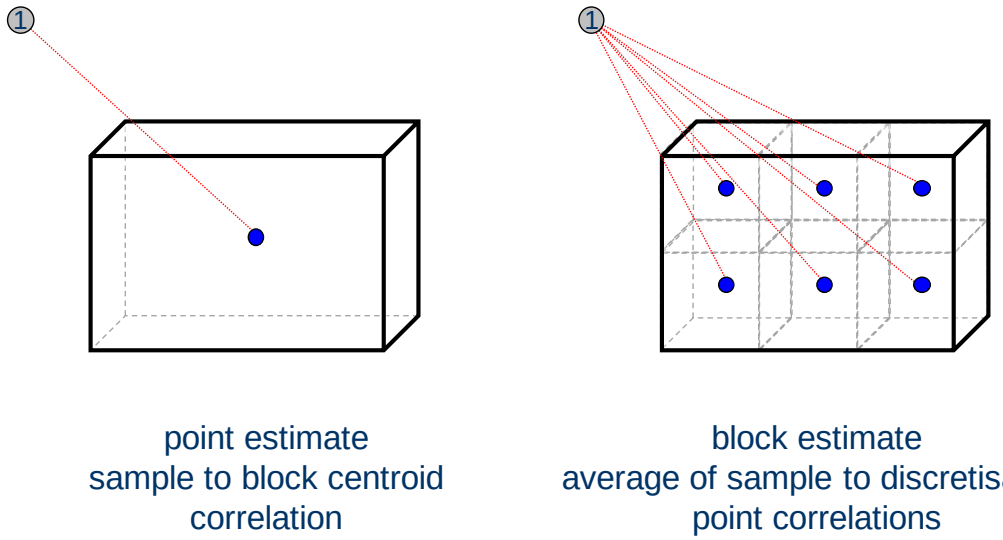
Discretisation

Discretisation is a means of correcting the estimate for the volume variance effect. Rather than estimating at a point in the centre of the block, the block is regularly divided into a three dimensional array of pseudo points or discretisation points.

For kriging estimates, the distance (and direction) between the sample location and each discretisation point is measured. Instead of reading a single variogram value for the sample to block distance (and direction), the variogram values between the sample and all the discretisation points are collected and averaged. This averaging process creates estimates that are identical to estimating point estimates at the pseudo points and averaging them to create a block estimate. Increasing the number of discretisation points will slow the estimation process exponentially.

Discretisation points are generally defined in terms of number or spacing in each of the three block dimensions; easting, northing and elevation. Figure 4.20 shows the difference between a point estimate and a block estimate using a discretisation of 3 by 2 by 1.

Figure 4.20 Discretisation



Thirty or more discretisation points should ideally be used for each block so that the volume variance is correctly accounted for. It is good to take into account the anisotropy of your blocks as well as your composite size. For example, for a 20 mE by 40 mN x 4mRL block with 2 m composites you might select discretisation points numbering 4 E by 8 N by 2 RL (total of 48 points).

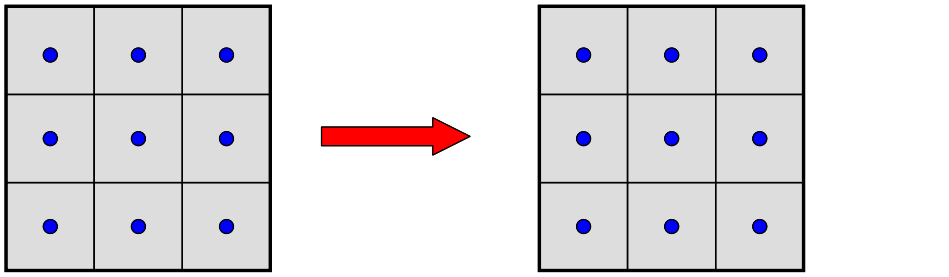
The number of discretisation points can also be optimised using conditional bias statistics as discussed in section 4.5.

Parent cell estimation

When building a block model it is common practice to use subcells to better delineate domain boundaries. The problem here is that the parent cell size is generally the optimal size for estimation, and hence estimation into smaller subcells will be suboptimal.

The answer to this problem is to use parent cell estimation. This means that the estimation process will treat all subcells within a parent cell as one block for estimation purposes and they will all receive the same grade estimate (Figure 4.21).

Figure 4.21 Parent cell estimation

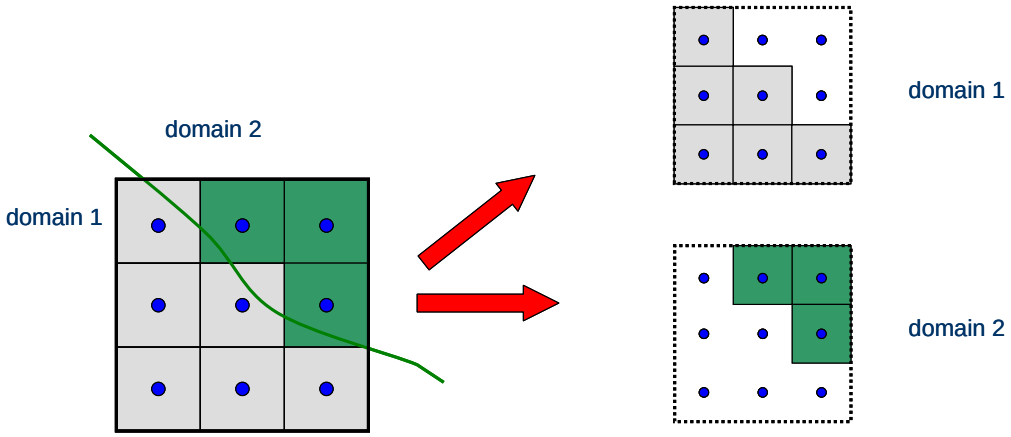


subcelling within parent cell - one domain

1/ estimate using all discretisation points
2/ assign estimate to all subcells

If there is more than one estimation domain coded within a parent cell, then the full parent cell is used for estimation of each domain (i.e. the full grid of discretisation points) and the resultant grade assigned to the applicable portion. Figure 4.22 illustrates this process for a parent cell comprising two domains.

Figure 4.22 Parent cell estimation for multiple domains



subcelling within parent cell - two domains

1/ use domain samples only
2/ estimate using all discretisation points
3/ assign estimate to domain subcells only

Kriging weight anomalies

Under certain circumstances the kriging process can result in anomalies in the assignment of the kriging weights. These anomalies include issues of negative kriging weights being assigned to samples, and closer samples receiving lower kriging weights than distant samples.

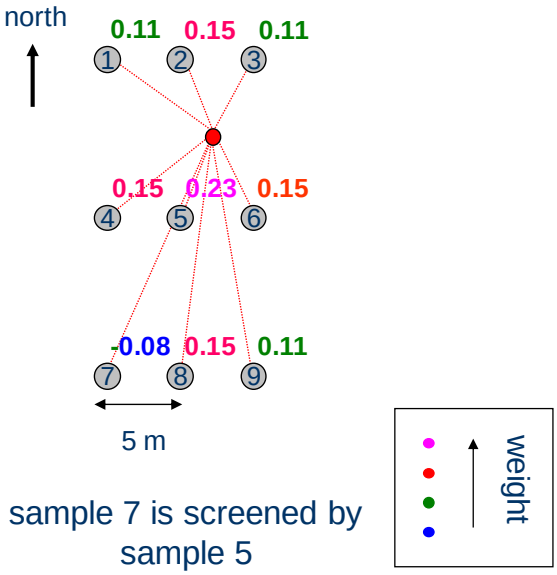
While negative kriging weights are mathematically correct, they can cause issues in grade estimation with the potential for negative grade estimates if the weights are assigned to a high grade sample. The main contributor to the assignment of negative kriging weights is clustering which results in what is termed screening.

The second anomaly type occurs if there is a trend in the domain (non-stationarity) which will result in a poor estimate of the local grade. This effect can result from extreme levels of anisotropy in your search ellipse or strings of data as discussed below (the string effect).

Screening

In cases where one sample is screened behind another sample, a negative weight may be assigned to the screened sample (Figure 4.23). This effect is the worst when the variogram has high continuity and a low nugget effect.

Figure 4.23 Kriging weights showing the screen effect

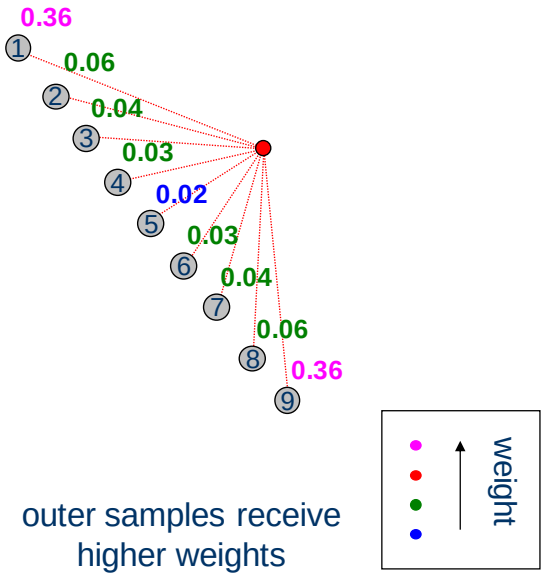


The string effect

Strings of data, such as drillhole results with continuous composites downhole, can cause strange configurations of kriging weights where the samples furthest away from the point of estimation receive the largest weights and the closest ones receive smaller or negative weights. This is called the string effect (Figure 4.24).

As with the screen effect, the string effect is worst when the variogram has high continuity and a low nugget effect. The string effect is only an issue when there are a small number of strings (drillholes) inside the search range. Once more than three or four drillholes are included, the issue becomes less significant.

Figure 4.24 Kriging weights showing the string effect



What to do with negative kriging weights and negative estimates

Always monitor the number of negative weights being produced during estimation. If there are more than a couple of percent, then look at ways of reducing them. Most software will create some sort of output file for checking the kriging weights applied.

Always check the final estimate for any negative grades. If there are a small amount of negative grade estimates it is reasonable to reset them to zero or below detection limit grade. Review where the negative grades estimates are and make sure that this is sensible before resetting.

Negative kriging weights are reasonably common during estimation and a small percentage of them should have a minor impact on the final estimate.

The kriging variance provides a relative measure of data coverage. For this reason, it is useful as a guide for resource classification.

Estimation parameters

In order to carry out an ordinary kriged estimate the following information is required:

- Composited drillhole file coded with estimation domains and top cut if appropriate.
- Three dimensional block model coded with estimation domains.
- Search neighbourhood parameters including search ellipse and minimum and maximum number of informing samples for estimation.
- Sample weighting information from variogram models for each domain.
- Number of discretisation points for estimation.
- Field names which, dependant on the software being used, may include: input drillhole grade field, output grade field for estimate, search pass, number of informing samples, distance to closest informing sample, kriging variance, kriging efficiency, slope of regression, LaGrange multiplier and within block variance.

Kriging estimates are controlled by the estimation parameters. The effect on estimation of some of the key parameters are summarised below.

- Nugget effect:
  - Higher nugget effects smooth out the kriging weights and leads to smoother estimates. These estimates have higher kriging variances and hence lower confidence.
  - Lower nugget effects cause more weight to be assigned to the closer data values and are hence more responsive to local data values. Typically low nugget effect models are more selective as there is less smoothing in the estimation process.
- Variogram range:
  - Weights are smoothed out when ranges are increased, resulting in a smoother estimate.
- Maximum number of samples:
  - Lower maximum number of samples results in a more selective estimate.
  - Higher maximum number of samples results in a smoother estimate.

Considerations for multi element estimation

When dealing with multi element estimation, it is important to try and maintain the correlations between the attributes. Independent kriging of attributes does not maintain correlations; however, there are some basic guidelines which will minimise the problem.

Tips for maintaining correlation during estimation include:

- Determine correlation coefficients between the attributes.
- Think about the correlation coefficients when modelling variograms. If attributes are correlated then they should behave in a similar manner spatially. Model the attributes with the best structured variograms first and then use the correlations as a guide to modelling the other attributes. Note if two attributes have a correlation coefficient >0.9, the variogram models should be almost identical.
- Where possible, model variograms in the same orientation for all attributes. If there is a less than 10º difference in orientation, pick the average or the stronger trend.
- Ensure that the same search neighbourhood (orientation, ranges and number of samples to use for estimation) is used for all attributes being estimated. This will ensure that the same samples are selected for the estimation of all attributes into a block.
- In some cases the search neighbourhood may need to be sub-optimal for some attributes. Base the search neighbourhood on the main economic attribute or use an average, best case for all attributes.

It is good practice to determine correlation coefficients between the estimated attributes and compare these to the original correlation coefficients from the sample data for each domain. This will highlight if there are potential issues.

4.4.6 Two dimensional estimation

Two dimensional (2D) estimation techniques have been historically and are still used in South Africa for many of the Witwatersrand alluvial gold channel deposits, and more recently the chrome and PGE deposits of the Western and Eastern Bushveld Complex. These methods are applicable to flat tabular ore bodies such as coal, alluvial deposits or layered intrusions.

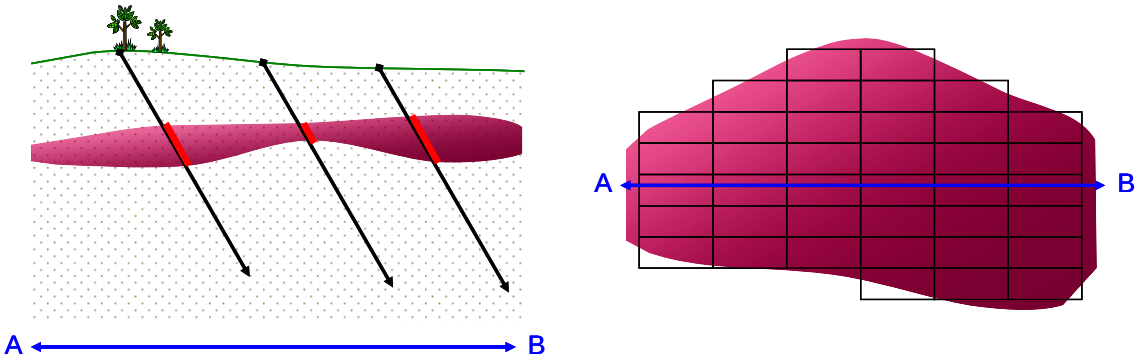
As the name suggests, 2D models are ‘flat’ meaning there is no grade variability in the third dimension. The thickness of the domain is estimated along with the grade attributes.

The primary requirements for 2D estimation are:

- The thickness must be amenable to estimation.

- Compositing must be carried out over the domain (one composite per intercept, Figure 4.25, left).
- It must be possible to describe the domain with a single layer of blocks (Figure 4.25, right).

Figure 4.25 Compositing and block model for 2D estimation of flat, tabular ore body

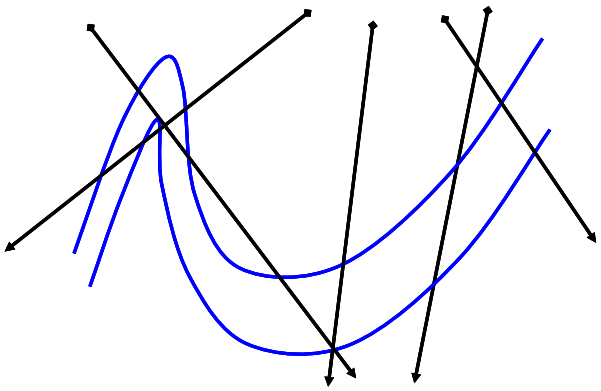


cross section view with drillhole composites

plan view with 2D blocks

2D estimation can be very difficult to apply, or impractical, in domains with complex geological structures or multiple drillhole orientations as it is difficult to convert these domains to 2D and to calculate thickness.

Figure 4.26 Complexity and 2D estimation



how to make a 2D block model?

how to calculate width?

2D techniques lend themselves to accumulation estimates which address the issues of variable support (volume) due to varying sample lengths. Accumulation is recommended when there is a strong negative correlation between grade and thickness.

Accumulation variables are calculated by multiplying the grade attributes by the thickness (grade x thickness). Thickness is kriged together with the accumulation variables. The thickness estimate is then used to back calculate the grades in the blocks from the accumulation variables.

It is important to use the same variograms, search neighbourhoods and estimation parameters for the accumulation variables and thickness.

It may be appropriate to density weight as well as thickness weight the accumulations to address issues of variable sample support due to density changes. This is referred to as a triple accumulation (grade x thickness x density).

Important considerations for 2D accumulation estimates include:

- Any estimation of a narrow tabular deposit is potentially a compromise.
- 2D accumulation tends to smooth the local block tonnage. If local estimates are required use an inverse distance squared or cubed estimation method; do not rely on the kriged thicknesses.
- Back calculated grades can be inconsistent compared to the input data.
- Careful checking is always essential.

4.4.7 Simple kriging

Simple kriging assumes that the mean grade of the domain is known and reasonably constant throughout the domain, hence the method requires strict stationarity. Simple kriging uses the same kriging equation as ordinary kriging but assigns a weight to the mean grade of the domain. This means that the kriging weights do not necessarily sum to one and in areas of sparse drilling the estimates will tend towards the mean grade.

Simple kriging minimises conditional bias more than ordinary kriging and is the preferred estimation method when carrying out conditional simulation, however the requirement for strict stationarity limits its usefulness in many deposits.

4.4.8 Indicator kriging

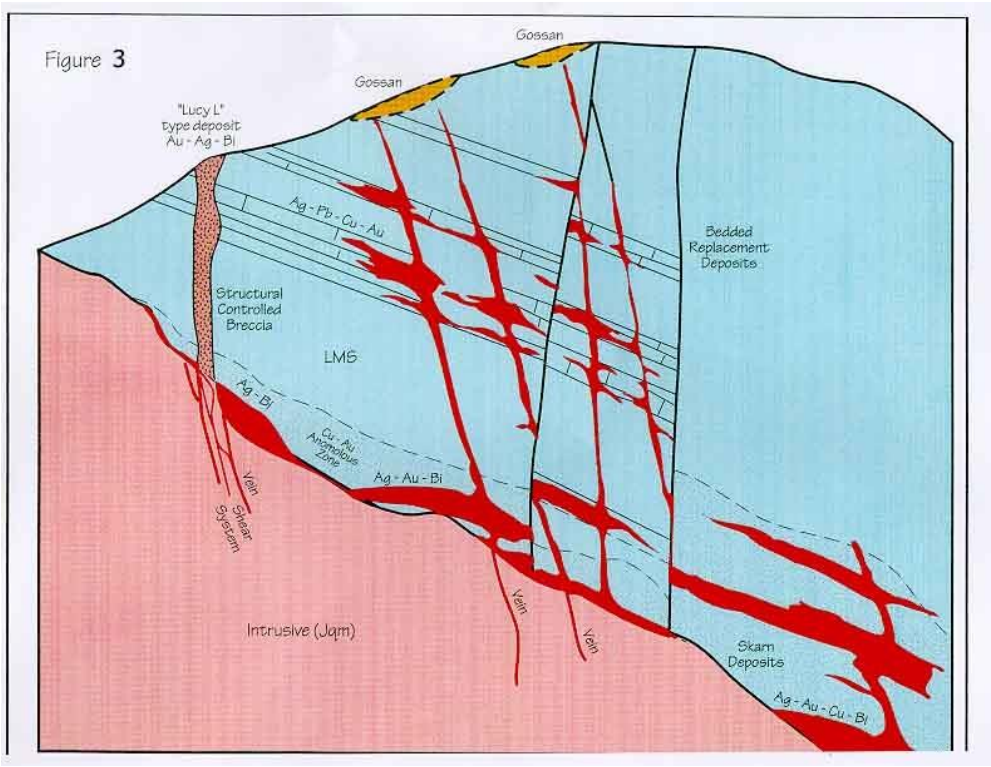
Many geostatistical methods including ordinary kriging are parametric (assumes data from a particular distribution). Failure to ensure the underlying statistical assumptions are met when applying parametric methods can result in a poor, biased estimate.

Some geostatistical methods such as indicator kriging are non-parametric and hence do not assume any population distribution. These methods are useful for dealing with mixed or highly skewed datasets (Figure 4.27).

Indicator kriging should never be used as a replacement for domaining. The underlying assumption when applying indicator kriging to mixed populations is that the populations are physically integrated and cannot be separated by domaining.

The indicator kriging process is described below. The process is illustrated at each step using the nine sample example used previously.

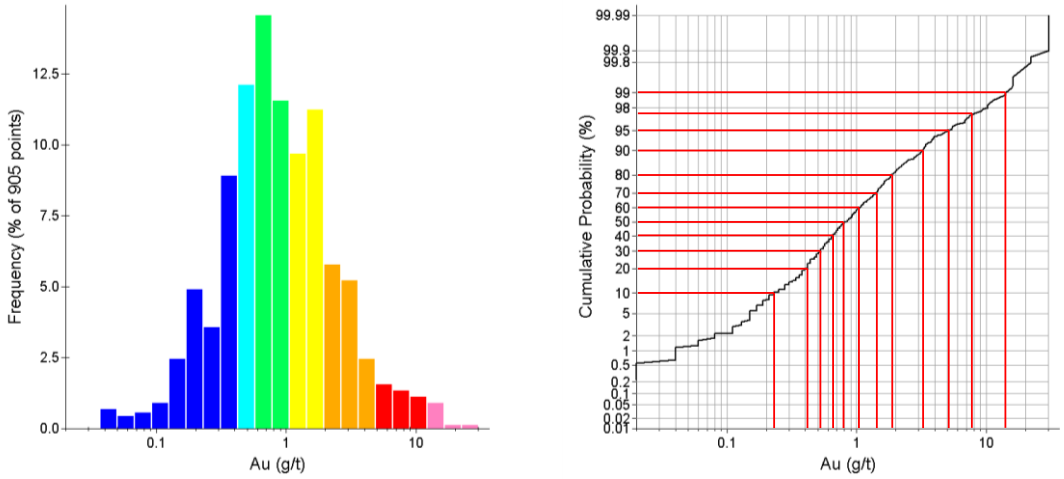
Figure 4.27 Mixed orientation examples



Indicator threshold selection

Indicator kriging requires the data distribution to be described using a series of indicator cut-offs or thresholds. The indicators used are typically the deciles (10^{th}, 20^{th}, 30^{th}, 40^{th}, 50^{th}, 60^{th}, 70^{th}, 80^{th} and 90^{th} percentiles of the data distribution), inflection points in the population distribution and some extra percentiles at the high grade end to control metal content (commonly 95^{th}, 97.5^{th} and 99^{th} percentiles). Sufficient indicators are required to fully map the population distribution and it is good practice to ensure that no more than around 10 to 15% of the samples or of the metal are contained between any two indicator thresholds (Figure 4.28).

Figure 4.28 Case study showing indicator threshold selection



log histogram log probability plot

For the nine sample example used below, it has been assumed that this population can be adequately represented by three indicator thresholds (0.95, 1.9 and 3.2 g/t Au).

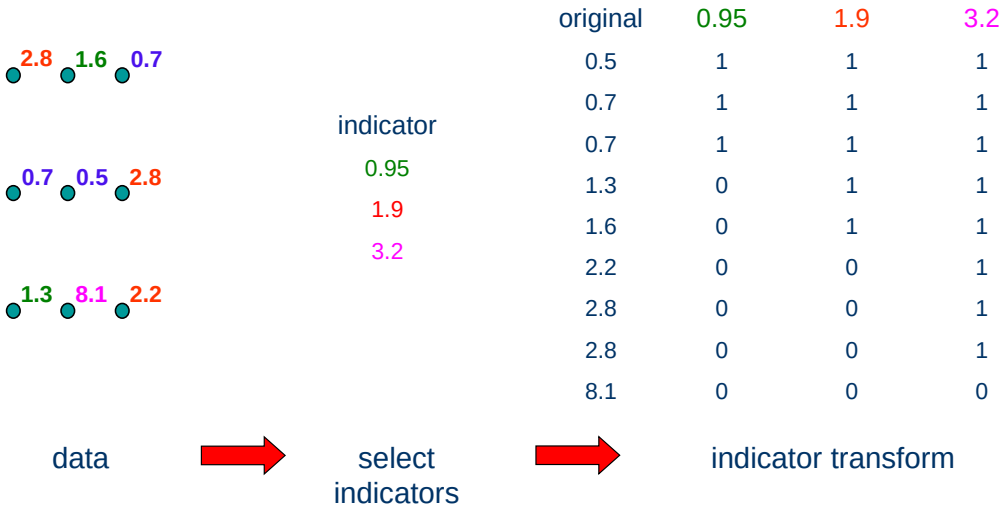
Indicator data transformation

The indicator transform is carried out by coding the data above and below a given value or indicator threshold. Every sample grade is coded for all specified indicator thresholds. The indicator code for a sample value at a specified threshold is set to:

- One if the sample grade is less than or equal to the threshold grade.
- Zero if the sample grade is greater than the threshold grade.

In our example, the nine sample values are coded at each indicator threshold according to the above rule (Figure 4.29).

Figure 4.29 Worked example - indicator data transform

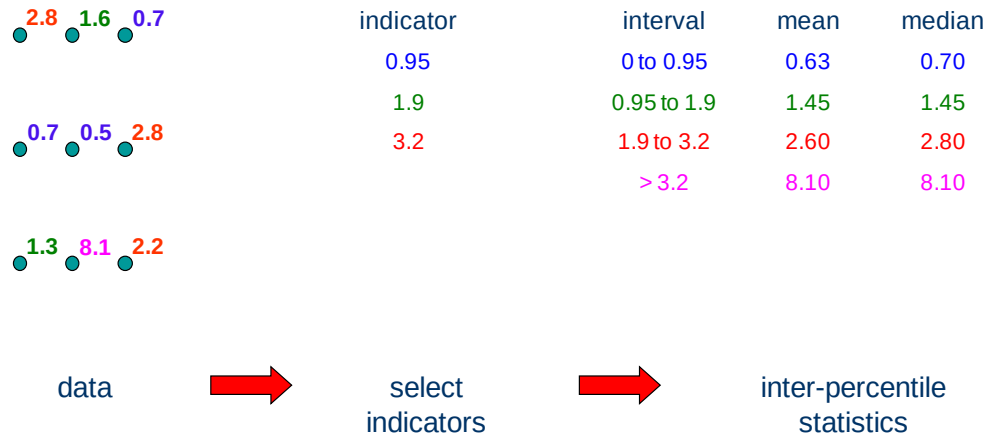


Inter-percentile statistics

The mean and median grade can be assessed for the sample data lying between each indicator threshold to provide a measure of the typical grade at a range of grade intervals. These inter-percentile statistics are used during the indicator kriging process.

Figure 4.30 shows a worked example of inter-percentile statistics for the nine samples. Assuming that this nine sample population can be adequately represented by three indicators (0.95, 1.9 and 3.2 g/t Au), the mean and median have been calculated for each inter-percentile range. Note that the samples and statistics are colour coded based on the indicators.

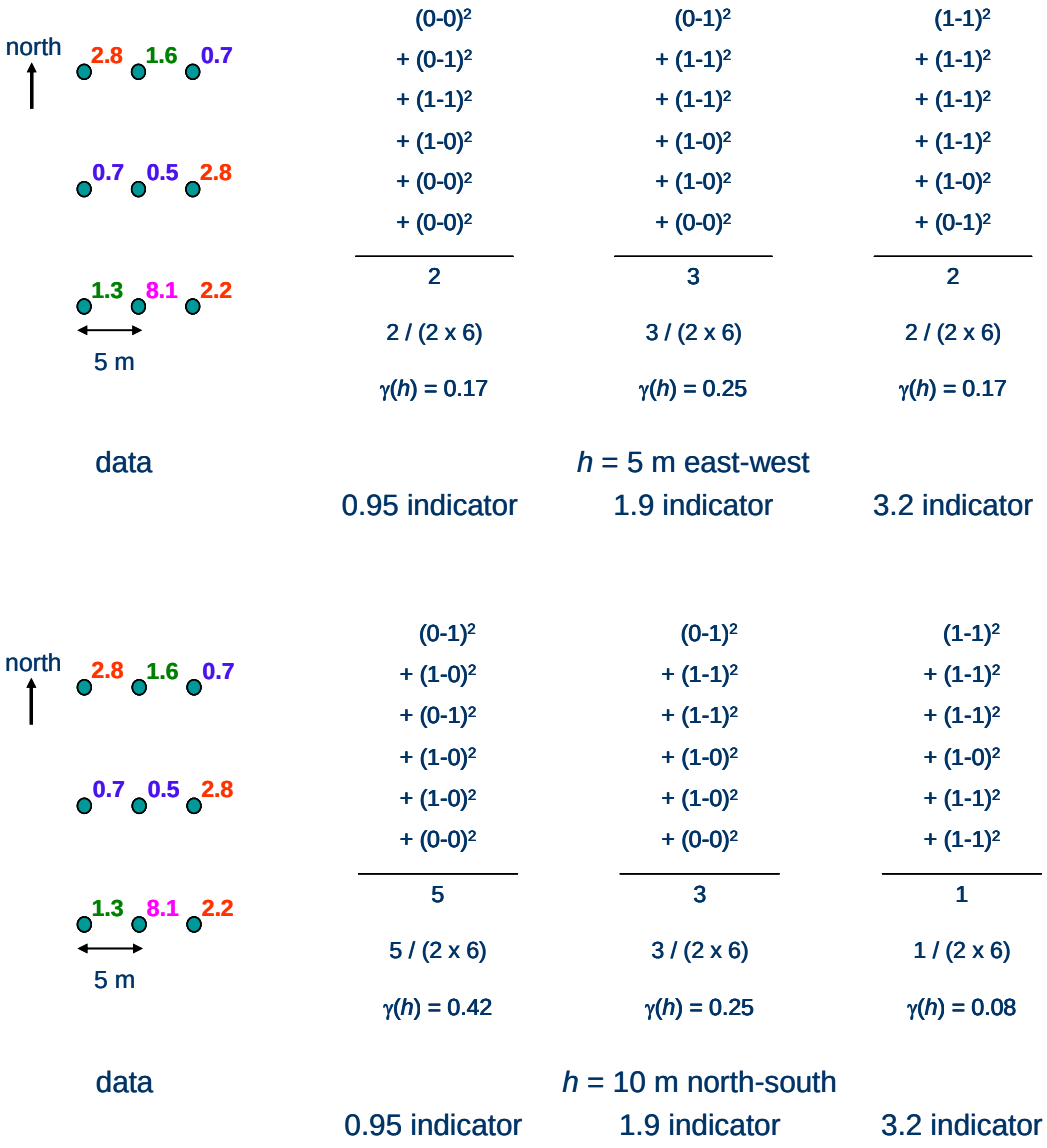
Figure 4.30 Worked example – indicator statistics



Indicator variogram calculation

Once the data is transformed into zeros and ones, then the variogram calculation is carried out on the transformed data for every indicator. Figure 4.31 shows the variogram calculations for the example above using a 5 m east-west lag and a 10 m north-south lag.

Figure 4.31 Worked example - indicator variogram calculations

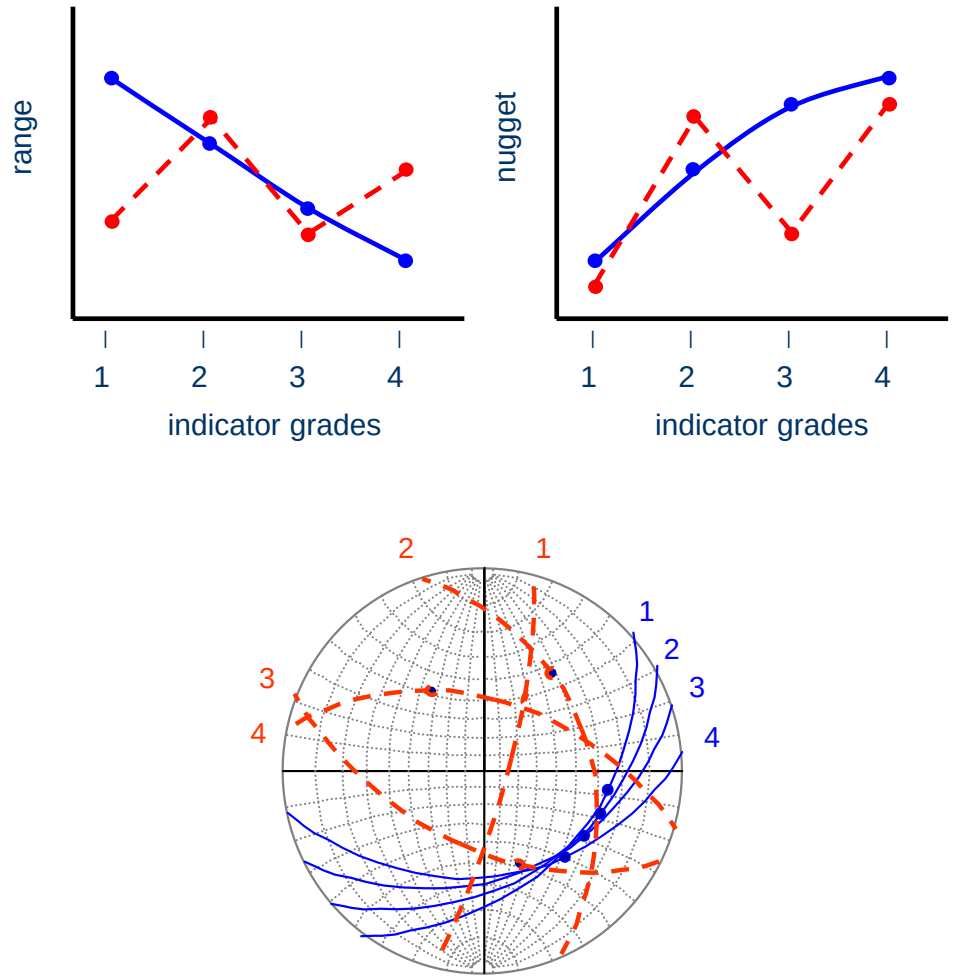


Modelling indicator variograms

Indicator variograms for each indicator threshold are modelled in the same way as traditional variograms. The important difference is that the indicator variograms should not be modelled independently of each other. The nugget effect, sills, ranges and directions of continuity should vary smoothly with the changing indicators. Randomly varying parameters will cause what are called order relation problems during estimation.

Indicator kriging estimates the probability of a block being below the indicator threshold grade. This probability should logically increase with increasing cut-off grade. Order relation problems are due to the independent estimation occurring at each indicator threshold which can result in a higher threshold having a lower probability than the one before. Order relation problems can be minimised by ensuring that the variogram parameters smoothly vary as illustrated by the blue lines in Figure 4.32.

Figure 4.32 Minimising order relation problems

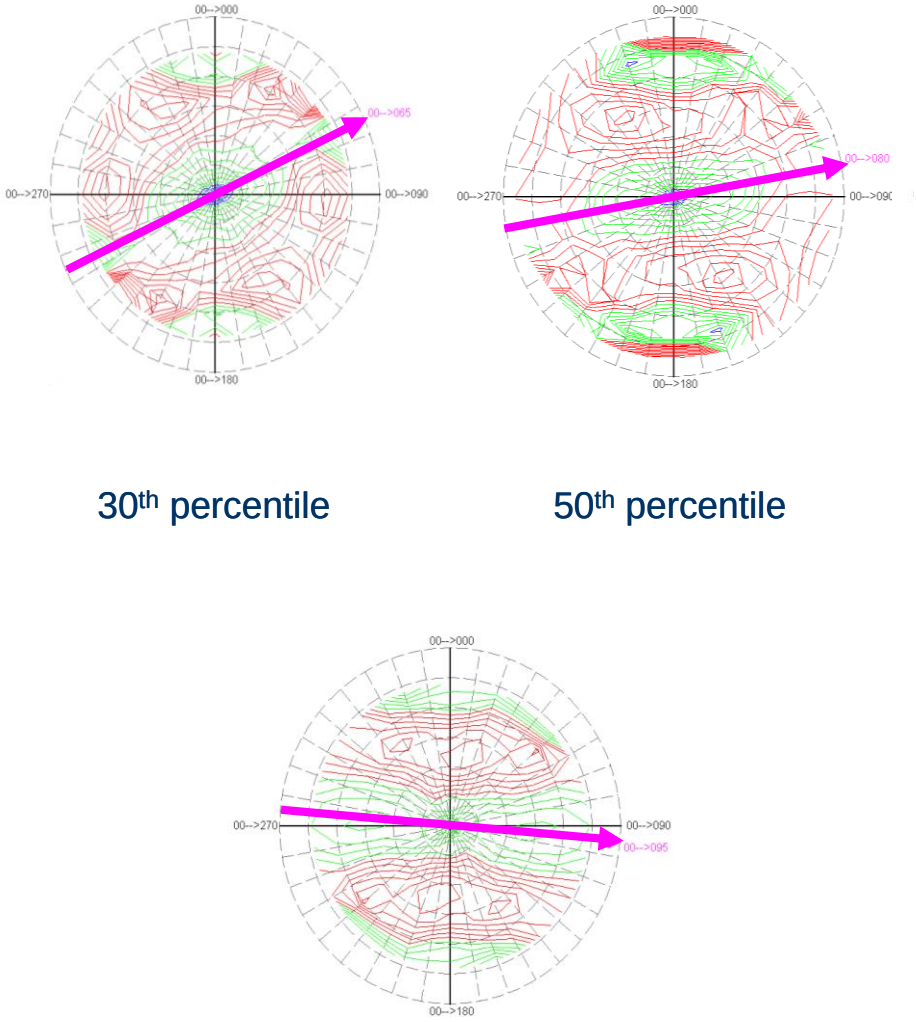


Case study 1 – indicator variograms for rotating anisotropy

The geology of a sulphide nickel deposit indicated that there were different structural controls on low and high grade mineralisation, even though there was a single mineralisation population in the domain.

Indicator variogram fans confirmed that there is “rotating anisotropy” of directions of mineralisation continuity, where the lower grades are orientated differently to the higher grades (Figure 4.33).

Figure 4.33 Case study showing indicator variogram fans with rotating anisotropy



Case study 2 – indicator variograms for structural complexity

Cross cutting structural controls were modelled in the geology of a gold deposit in northern Western Australia. Multiple phases of mineralisation and remobilisation were believed to have generated a complex interlacing of mineralisation that was impossible to domain into spatially distinct zones.

The normal scores variogram fan shows two directions of mineralisation continuity (Figure 4.34). The indicator variograms on the same dataset show that the northwesterly continuity is associated with the lower grades, while the northeasterly continuity is associated with the higher grades (Figure 4.35).

Geologically, the mineralisation is associated with cross cutting structures. The indicator variography is able to provide evidence of this association that can assist local estimation as well as further exploration.

Figure 4.34 Case study showing normal scores variogram fan for domain of structural complexity

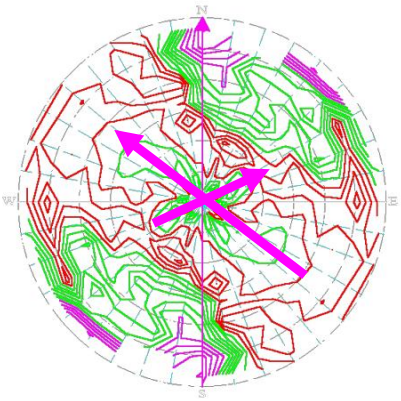
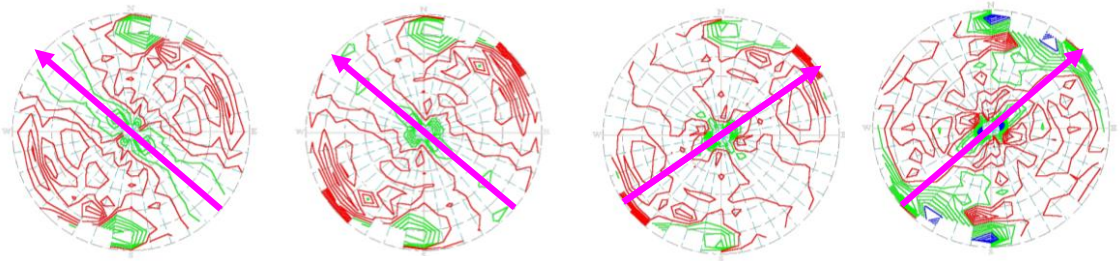


Figure 4.35 Case study showing indicator variogram fans for domain of structural complexity



0.6 g/t indicator | 1.0 g/t indicator | 1.5 g/t indicator | 3.0 g/t indicator

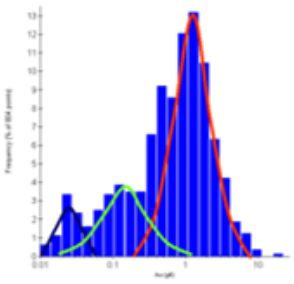
Case study 3 – stereonets for structural complexity

This mineralisation from the previous case study comprises three spatially integrated mineralisation populations (Figure 4.36). The tabulation of orientations of the gold mineralisation is difficult to visualise. However when these orientations are plotted on a stereonet, a pattern is evident (Figure 4.37):

- Low grades (greys and blues) dip to the north.
- Medium grades (greens) dip to the east.
- High grades (magenta) dip to the northwest.
- Plunge orientations occur at intersection of dip planes.

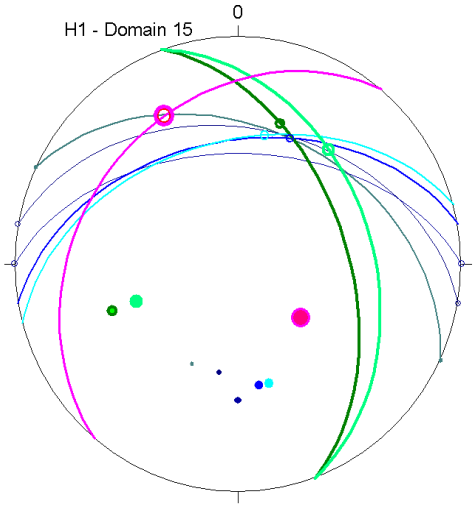
The stereonet is a useful tool for communicating and verifying orientations against structural knowledge.

Figure 4.36 Case study showing mixed populations and orientations in a domain of structural complexity



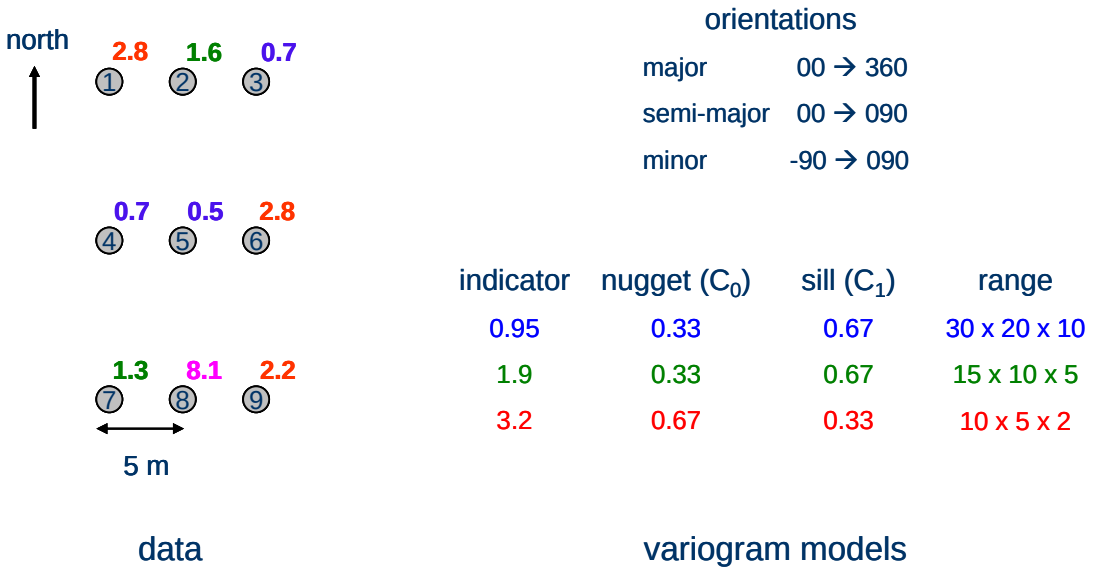
percentile	cut-off (g/t)	strike	dip	plunge
10%	0.12	295	-40-->025	00-->295
20%	0.19	280	-40-->010	00-->280
30%	0.27	270	-50-->000	00-->270
40%	0.45	260	-45-->350	-40-->023
50%	0.67	255	-45-->345	-42-->012
60%	0.95	340	-50-->070	-36-->017
70%	1.52	340	-40-->070	-36-->039
80%	3.84	220	-30-->310	-28-->333
90	5.25	220	-30-->310	-28-->333

Figure 4.37 Case study showing structural complexity on a stereonet



For the worked example, the following variogram models have been assumed for the three indicator thresholds.

Figure 4.38 Worked example – indicator variogram models

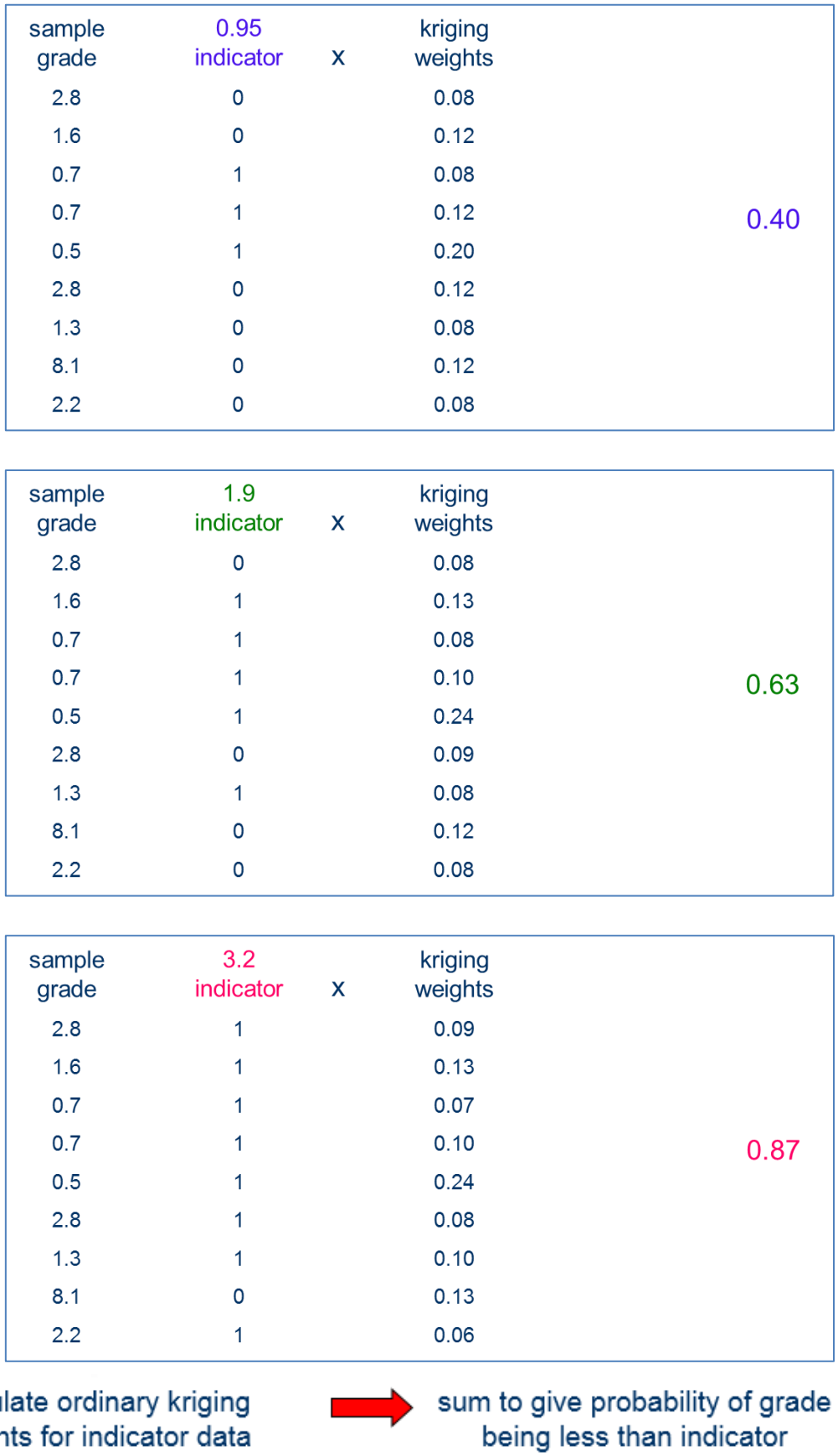


Indicator estimation

Estimation is carried out using ordinary kriging of the transformed data (1 and 0 values) and appropriate indicator variogram for each indicator threshold (Figure 4.39). The result is an estimated value between 0 and 1 for each indicator which is the probability that the grade will be less than the indicator threshold grade.

These probabilities create a CDF at each estimation point which describes the full range of grades and the corresponding likelihood that the grade will be less than any given grade.

Figure 4.39 Worked example – ordinary kriging of indicators

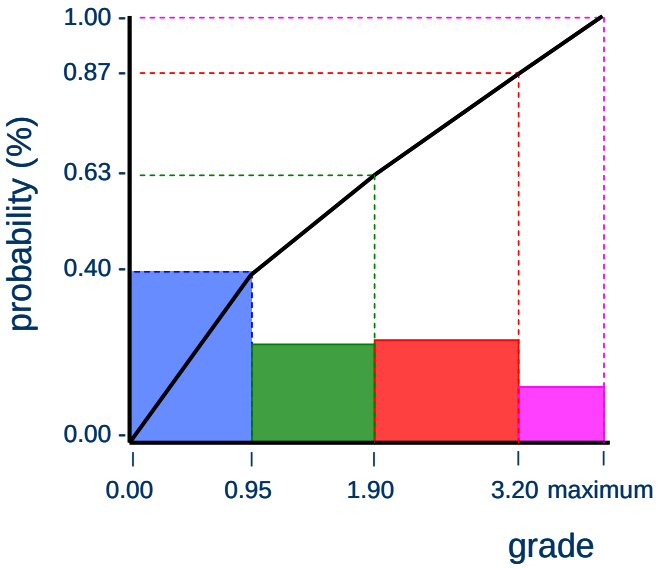


Grade calculation

The probabilities that the grade will be less than the indicator grades are converted to the probabilities that the grade will be in the intervals between indicator grades. This is carried out by simply subtracting the probability of being less than the lower interval grade from the probability of being less than the higher interval grade.

This is repeated for all intervals to create the equivalent of a histogram of likely grades for the estimation location (Figure 4.40).

Figure 4.40 Worked example – CDF and histogram of probabilities from estimation of indicators



Grades are assigned to each interval using the mean of the interval. The final indicator kriged estimate of the expected grade at a particular location is then generated by multiplying each interval mean grade by the probability that the location will have a grade in the interval, and summing the results (Figure 4.41).

indicator kriged estimate = sum of (sample grade x probability)

Figure 4.41 Worked example – calculating grade in indicator estimation

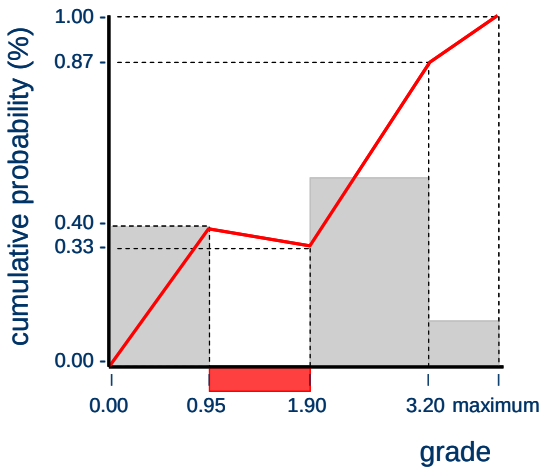
		estimated probability			statistics		calculated
indicator	interval	grade being < indicator	grade being within interval		mean grade within interval		grade within interval
0.95	0 to 0.95	0.40	0.40	x	0.70	=	0.280
1.9	0.95 to 1.9	0.63	0.23	x	1.45	=	0.334
3.2	1.9 to 3.2	0.87	0.24	x	2.80	=	0.672
	> 3.2	1.00	0.13	x	8.10	=	1.053
							2.339

Note: When there is a positively skewed tail and the mean grade of the last interval is calculated from a small set of data, then the mean grade will be biased by a few extremely high grades. In this situation, the median grade is believed to provide a better representation of the grade conditions and so is used in place of the mean grade for the last interval. Another option is to fit a mathematical model to the upper end (head) or the CDF and use this to model the grade.

Order relation corrections

Because each indicator probability is estimated independently with possibly different sets of parameters, it is possible to generate non-increasing cumulative probabilities (Figure 4.42). These non-increasing probabilities result in negative probabilities within intervals which are called order relation problems.

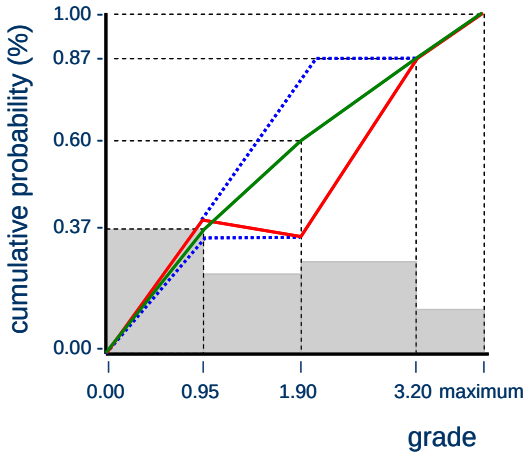
Figure 4.42 Order relation problem



The indicator CDF can be corrected to ensure non-negative probabilities (Figure 4.43). The recommended method for applying corrections is the upward-downward (average) correction where the cumulative probabilities are adjusted to the average of:

- An upwards correction - the downward trending cumulative probability value is increased to the value of the next highest indicator's cumulative probability.
- A downwards correction - the cumulative probability value for the indicator previous to the downward trending value is decreased to the value of the downward trending cumulative probability.

Figure 4.43 Order relation correction



As discussed previously, in order to minimise order relation problems, indicator variograms should not be modelled independently of each other. The nugget effect, sills, ranges and directions of continuity should vary smoothly with progression through the indicators. Randomly varying parameters will cause order relation problems during estimation.

4.4.9 Categorical indicator kriging

Categorical indicator kriging is an application of indicator kriging which can be used to assist in:

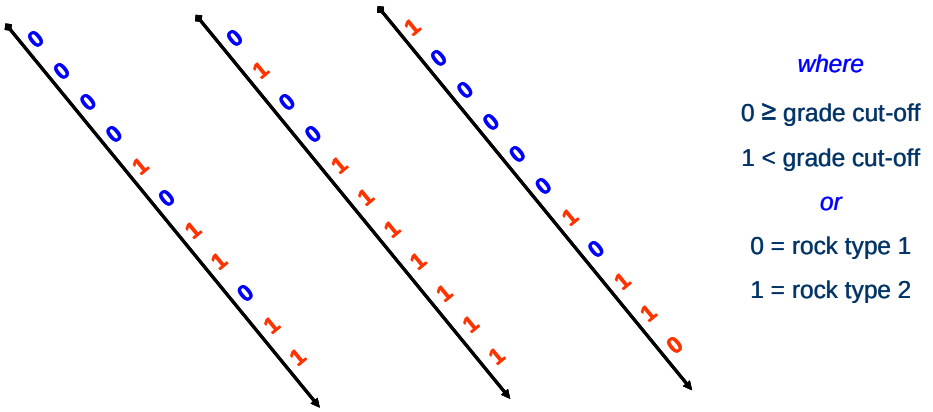
- Defining a grade domain boundary by estimating the probability of a block being above or below the cut-off grade.
- Defining geological domains by estimating the probability of a block containing a geological characteristic, for example, a rock type or alteration style (based on geological logging data).

The process is a simplified version of indicator kriging, but with only one indicator estimated. The method is described below, with an example where three drillholes are being used to estimate into a panel of blocks.

- Define the indicator criteria:
  - For a grade domain boundary decide on the cut-off grade of interest and use this as the indicator.

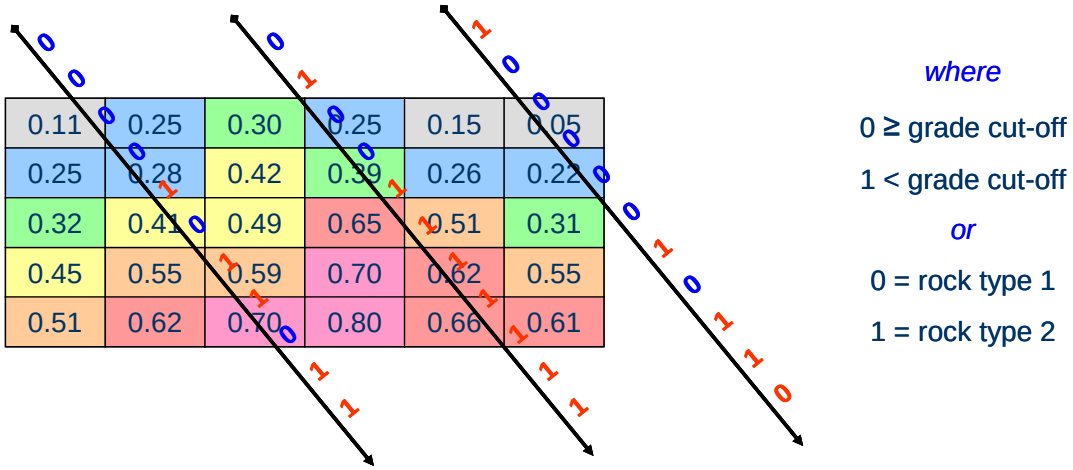
    For a geological domain select the geological characteristic of interest.
- Code the composited sample data (Figure 4.44):
  - For a grade domain boundary set to 1 if the sample grade is less than or equal to the indicator cut-off otherwise to 0.
  - For a geological domain set to 0 if the composite is logged as the geological characteristic of interest otherwise to 1.

Figure 4.44 Indicator coding of drillhole composites for categorical kriging



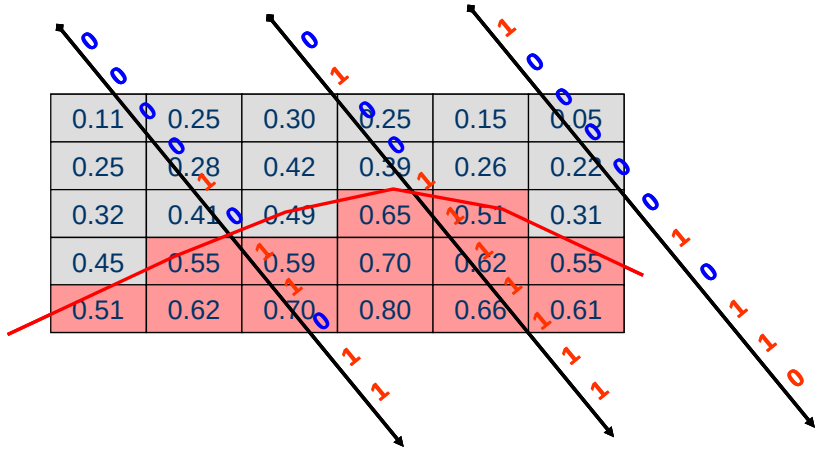
- Model a variogram using the coded data (1 and 0).
- Carry out ordinary kriging using the coded data and indicator variogram. The result is an estimated value between 0 and 1 which is the probability that the block grade will be less than the grade cut-off or that the block contains the geological domain (Figure 4.45).

Figure 4.45 Ordinary kriging of indicator codes for categorical kriging



- Review the resultant estimated probabilities, together with the input composites and select a probability threshold which best represents the domain boundary. This threshold can either be used to directly code the domains, or it can be used as a guide to interpreting a domain boundary (Figure 4.46).
  - The threshold of interest tends to lie around the 0.50 value. The probability estimate can also be used to assess risk and uncertainty in domain boundaries by selecting a more or less conservative threshold to define the boundary.

Figure 4.46 Domain definition for categorical kriging



Categorical kriging is particularly useful where there is uncertainty during interpretation. By modelling a variogram and using this spatial relationship between the domains to estimate probabilities, a three dimensional view of the domains can be defined.

4.4.10 Selecting an estimation technique

The basic statistics of the domained data are useful as a guide for selecting the most appropriate estimation techniques (Figure 4.47). Generally ordinary kriging is the best estimation method in all situations with the exception of mixed populations and highly skewed populations where indicator kriging is required.

Some of the main advantages and disadvantages of the methods discussed are summarised in Table 4.1.

Figure 4.47 Selecting an estimation method

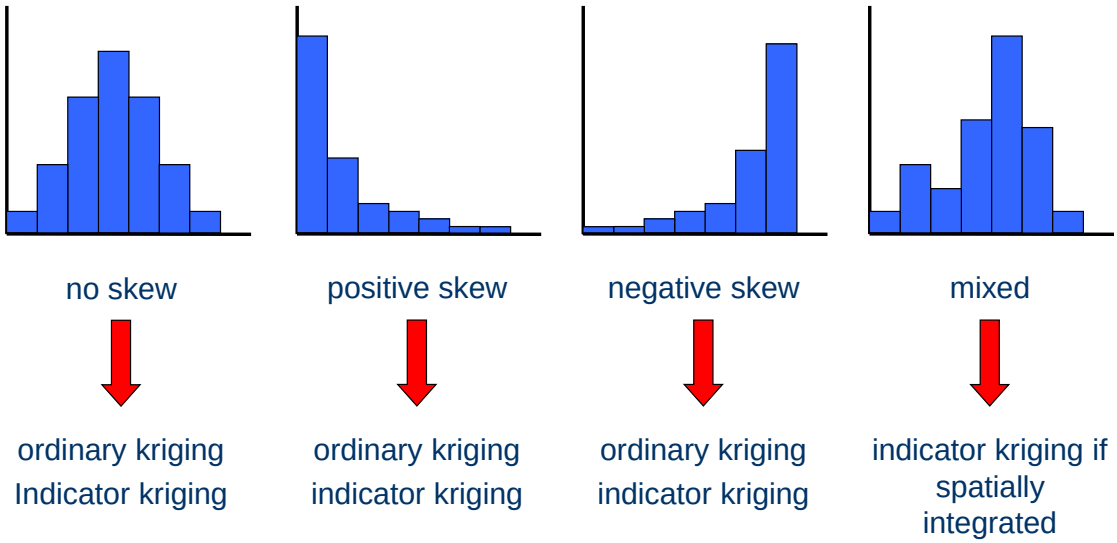


Table 4.1 Advantages and disadvantages of estimation techniques

Technique	Advantages	Disadvantages
Inverse Distance	Quick and easy to use. Only a few parameters to set.	Choice of power is arbitrary. Sensitive to data clustering. Weighting is directly related to distance, irrespective of ranges of influence.
Ordinary kriging	Uses spatial relationship between samples to weight the samples. Built in declustering.	Time and effort to do variography. Negative weights need to be controlled.
Indicator kriging	Adapts weights according to grade ranges. Allows estimation for spatially integrated populations. Allows estimation when continuity rotates according to grade ranges. Copes with highly skewed populations.	Time and effort to do full indicator variography. Indicators are estimated independent of each other. Order relation problems need to be controlled.

4.5 Optimising parameters

In order to minimise the estimation error, it is important to ensure that you use an optimal block size and optimal estimation parameters. While common sense and following a few sensible guidelines can aid this, there are also statistics which can help quantify the effectiveness of the estimation process. These statistics are called conditional bias statistics.

This section discusses the conditional bias statistics and how to use them for optimisation of block size, number of informing samples, search range and number of discretisation points. This optimisation process is sometimes called kriging neighbourhood analysis (KNA).

These statistics are useful as a guide but other practical considerations must also be taken into account. Sections 4.2.1, 4.3 and 'Discretisation' discuss the selection of block size, search neighbourhood and discretisation point parameters based on the combination of statistical optimisation, practical issues and common sense.

4.5.1 Conditional bias statistics

Conditional bias refers to the 'degree of over smoothing' (reduction in variance of grades) in the estimate compared to the true variance of grade in the deposit. The optimisation process aims to determine the block size and estimation parameters which minimise the conditional bias in the estimate.

There are two conditional bias statistics used for optimisation:

- Kriging efficiency (KE), which measures the effectiveness of the kriging estimate to reproduce the local block grade accurately.
- Slope of regression or conditional bias slope (SLOPE[4]), which summarises the degree of over smoothing of high and low grades.

The following variance statistics are used to establish the kriging efficiency and slope of regression:

[4] *Sometimes referred to as PSLOPE.*

- Kriging variance (KV) – is calculated from the variogram and the kriging weights assigned during estimation. It provides a relative measure of accuracy of the local kriged estimate with respect to data coverage. Grade does not impact on this statistic. This is discussed further 'Ordinary kriging' in Section 4.4.5.
- LaGrange multiplier (μ) –increases with extrapolation, poor data coverage and/or clustering.
- Block variance (BV) – measures the degree of difference (variance) between block grades. It is dependant on block size and range and will increase as block size decreases due to the volume variance effect.

Kriging efficiency

The kriging efficiency statistic measures the effectiveness of the kriging estimate to reproduce the local block grade accurately. It is calculated by comparing the kriging variance of a block with the theoretical variance of the blocks (the block variance):

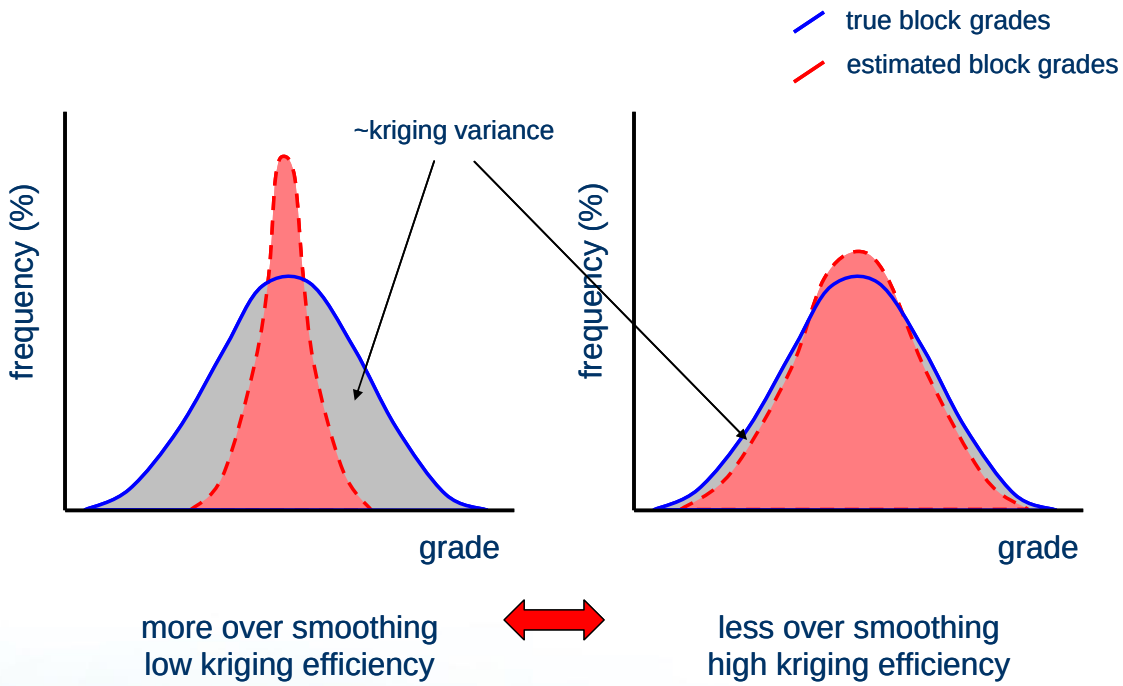
$$\textit{kriging efficiency} = \frac{\textit{(between block variance – kriging variance)}}{\textit{between block variance}}$$

When the kriging variance is small relative to the block variance then the kriging efficiency approaches a value of one. When the kriging variance is high and dominates the block variance (as would be the case for poorly estimated blocks) then the kriging efficiency will be low (sometimes even negative).

Low kriging efficiency indicates a high degree of over smoothing. Conversely, high kriging efficiency indicates a low degree of over smoothing (Figure 4.48).

Kriging efficiency is often reported as a percentage with the optimal value being 100% (1).

Figure 4.48 Kriging efficiency



Slope of regression

The slope of regression summarises the degree of over smoothing of high and low grades. This slope is equivalent to the regression slope of the estimated block grades against the corresponding true, but unknown, grades (Figure 4.49). The slope statistic is calculated as:

$$\text{Slope of regression} = \frac{(\text{between block variance} - \text{kriging variance} + \text{LaGrange multiplier})}{(\text{between block variance} - \text{kriging variance} + 2 \times \text{LaGrange multiplier})}$$

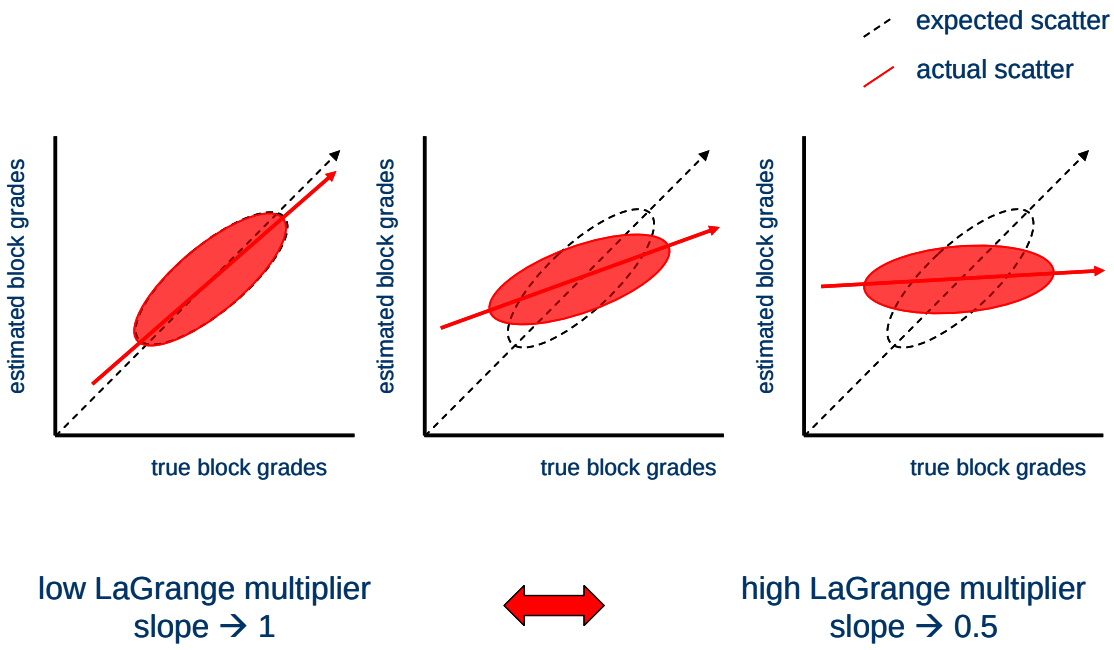
The LaGrange multiplier will be small when there is good data coverage, no extrapolation and limited clustering. In this situation the LaGrange multiplier is negligible compared with the rest of the equation and the slope statistic approaches one.

However, when the LaGrange multiplier is large (high degree of extrapolation, poor data coverage and/or clustering), then the LaGrange multiplier dominates the equation and the slope statistic tends towards a half.

A slope close to one indicates that the regression between the estimated and actual grades is likely to be very good, meaning there is limited over smoothing. In this case it is likely that the grade tonnage relationship above cut-off is realistic.

Conversely, low slope values indicate that there is over smoothing and hence a poor relationship between the estimated and actual block grades. In this instance it is unlikely that you will be able to accurately report selective estimates above a cut-off.

Figure 4.49 Slope of regression



4.5.2 Optimisation

The conditional bias statistics can be generated for any combination of estimation parameters and are typically used to optimise the block size, number of informing samples, search ellipse and number of discretisation points for estimation.

The method of optimisation is simply to run multiple kriging estimates using the appropriate variogram for the domain you are testing, with one parameter changed for each run. For example, increase the block size for each run.

While the total estimate can be run each time and the results averaged, this is often impractical. An alternative is to create a single block, or a small group of blocks, centred in the area you want to test. This should give you a representative result for this area. Centre the blocks between drillhole lines as anomalies can occur in the results if samples are directly adjacent to the estimation point.

It is recommended that several locations are tested to assess the impact of, for example, change in drillhole spacing, change in domain or change in grade tenor.

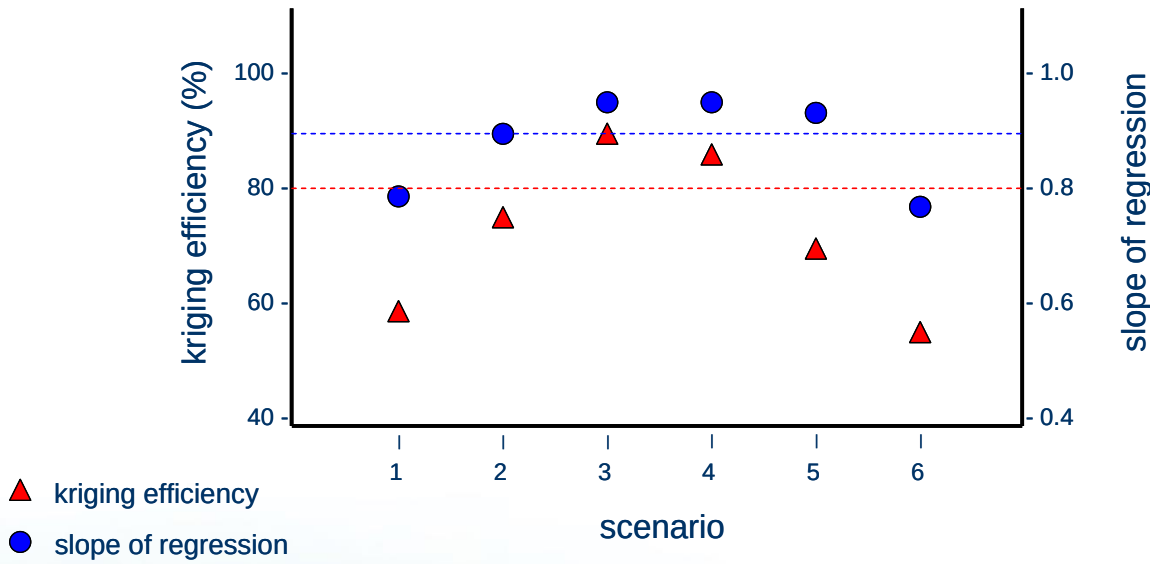
Once the estimates are run then, depending on the software, the kriging efficiency and slope can be extracted directly from the estimates or the kriging variance, block variance and LaGrange multiplier can be extracted and used to calculate the statistics.

Note, some mining software calculates the within block variance (f-factor), not the between block variance used in the kriging efficiency and slope calculations. In this instance the block variance can be calculated as the total sill of the variogram used for estimation minus the f-factor (Section 4.1.6).

Once the statistics are determined for each run, they can be plotted graphically and the runs with acceptable results highlighted (Figure 4.50). Ideally the optimal result is a slope of one and a kriging efficiency of 100%; however, this is never achievable in practice. More typical results are slopes of greater than 0.9 and kriging efficiencies in the order of 80% to 90%.

In areas of sparse drilling such as during the exploration stage, or in domains with short range grade continuity, the results will be lower. Additionally, in narrow domains the results will be poor due to the lack of data in the third dimension. This method can still be used in a relative sense to determine which scenario provides the better results.

Figure 4.50 Graphical output of parameter optimisation

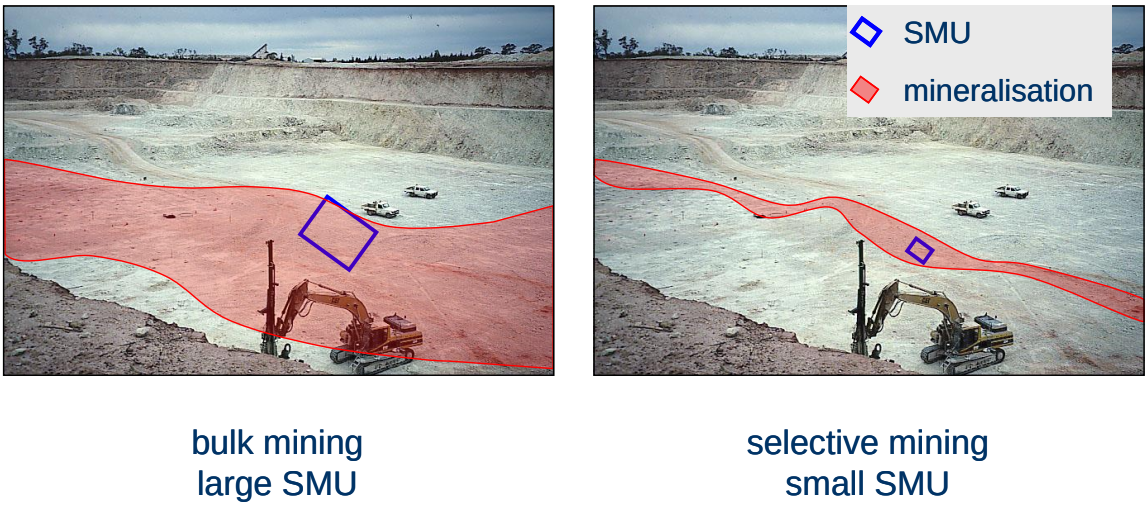


While these statistics are useful as a guide the decision should always be tempered by reality. After determining which runs provide acceptable results, think about the practical aspects of the choice. Given several options which give similar results, always select the result which makes the most sense in terms of mining and geological considerations (Figure 4.51).

There may be times when a reduced quality estimate must be accepted, for example, if the mineralisation is too narrow to adequately define the volume using the optimal block size.

If making any compromises, be sure to document them.

Figure 4.51 Reality check when optimising parameters



4.6 Density modelling

The importance of density in resource estimation is often overlooked. Density is a major risk item in terms of grade tonnage reporting and should be subjected to the same level of QAQC, validation and review as the grade attributes.

Common methods for modelling density include:

- Assignment of density values to the block model based on some combination of geological domaining such as oxidation state, rock type and mineralisation.
- Estimation of density in the same way as grade attributes. This is generally only useful if downhole density readings are available for all drillholes providing a comprehensive density dataset.
- Density is often correlated with grade attributes. This relationship can be used to calculate density based on the estimated grades.

When modelling density, consider the methods of density measurement and degree of confidence associated with these. Ensure that sufficient density measurements are available from each material type (oxidation state, rock type and mineralisation) to provide confidence in the results.

4.7 Validation

The validity of the grade estimates is subject to every decision made and parameter used throughout the resource estimation process. There are multiple points at which things can go wrong and hence it is essential to validate the final model to ensure that the estimated grades reflect the input information.

Several standard validation checks should be carried out for all grade estimates. The standard validation check list includes:

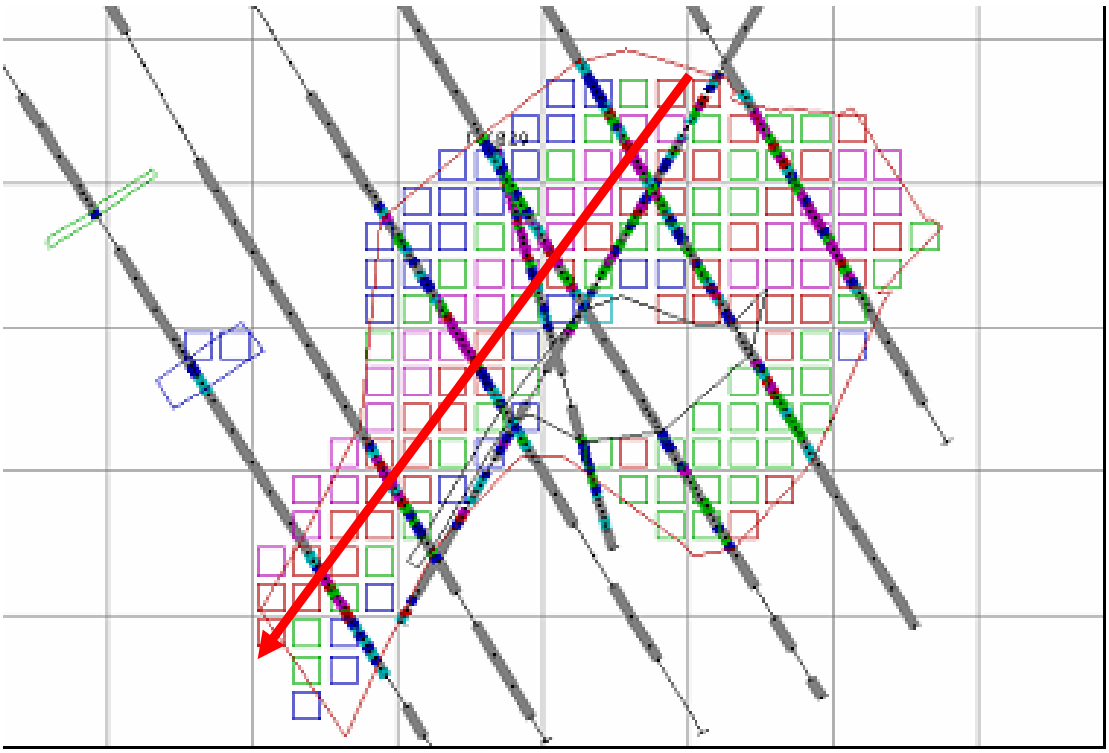
- Visual validation of the local trends.
- Global mean validation.
- Population distribution validation.
- Global trend validation.
- Global change of support.

4.7.1 Visual validation of the local trends

Step through the model and visually compare the estimates to the input composites. The estimates should reflect the local composites with some expected smoothing. Orientations observed in the variography should be reflected in the estimates.

The case study illustrated in Figure 4.52 shows an example of a visual validation where the estimated grades follow the expected trend of the mineralisation and reflect the drillhole grades reasonably well.

Figure 4.52 Case study showing visual validation with expected trend of mineralisation (red arrow)



4.7.2 Global mean validation

Statistical comparisons for each estimation domain should be carried out. The mean of the estimated grades should be similar to the mean of the input composites (declustered and top cut if necessary). It is a good idea to also look at the number of composites in each domain as domains with small numbers of composites will probably not validate as well as other domains.

A percentage difference field can also be shown for each domain; however, this can be misleading for very low grade attributes or domains.

The case study illustrated in Table 4.2 shows the global mean validation for a multi element estimate. In this instance the estimate comprises two domains and 12 attributes. All estimated attributes reflect the input composites reasonably well.

Table 4.2 Case study showing global mean validation

Attribute	Low grade domain		High grade domain	
	Model	Composites	Model	Composites
Al_2O_3	1.83	1.82	1.32	1.33
CaO	0.89	0.98	0.15	0.16
Fe	56.88	56.89	60.60	60.61
K_2O	0.031	0.032	0.008	0.008
LOI	8.65	8.54	8.43	8.35
MgO	0.15	0.14	0.09	0.09
MnO	0.28	0.24	0.26	0.25
Na_2O	0.04	0.04	0.03	0.03
P	0.05	0.04	0.06	0.06
S	0.06	0.07	0.02	0.02
SiO_2	4.82	4.96	2.59	2.64
TiO_2	0.07	0.06	0.05	0.05

4.7.3 Population distribution validation

Comparisons between histograms or cumulative frequency distributions of the input composites and the estimated grades for each estimation domain should show a similar population distribution. Remember, the estimated grades will be smoothed and hence will have a smaller variance and a compressed distribution compared to the input composites.

Figure 4.53 illustrates a case study where the histograms of the input composites compared to the ordinary kriging estimate (model 1) were reviewed as part of the validation process. The ordinary kriged estimate was carried out using a grade cut-off to define a higher grade domain within the mineralised package. The results show that the ordinary kriged estimate has a completely different population shape to the input composites and appears to have two distinct grade populations.

A subsequent indicator estimate (model 2) was run without the grade boundary constraint. This estimate shows a similar population shape to the input composites.

Figure 4.53 Case study showing population distribution validation

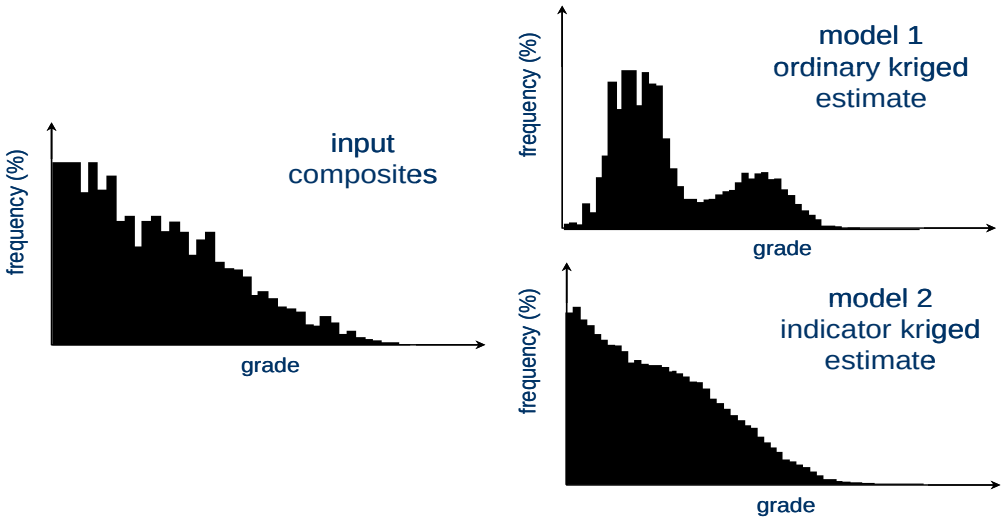
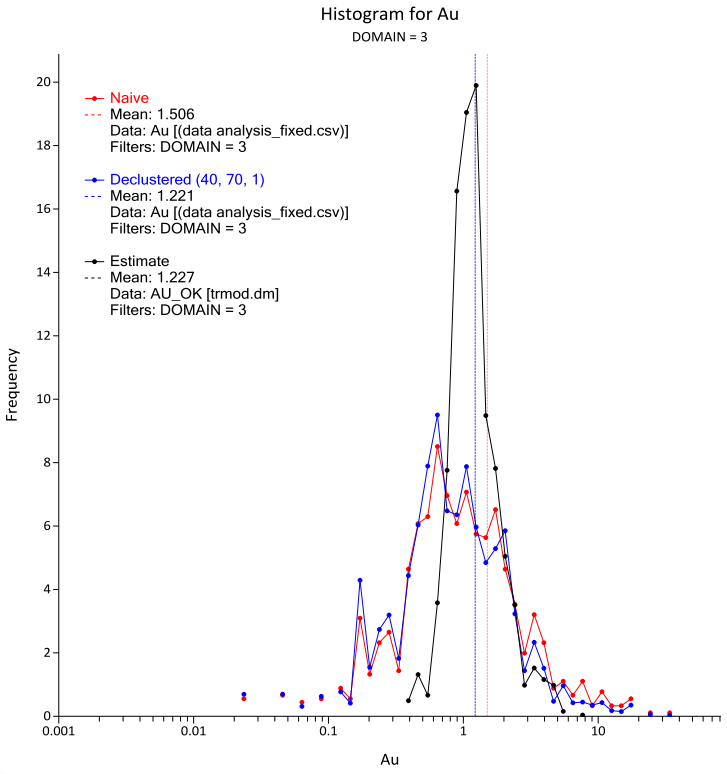


Figure 4.54 illustrates a case study where the log transformed histograms of the input composites, both naïve and declustered, are compared to the log transformed ordinary kriging estimate. The estimated grades show a 'narrower and higher' histogram because of the smoothing caused by estimating into the larger volume blocks.

Figure 4.54 Case study showing population distribution validation in Supervisor – log transform



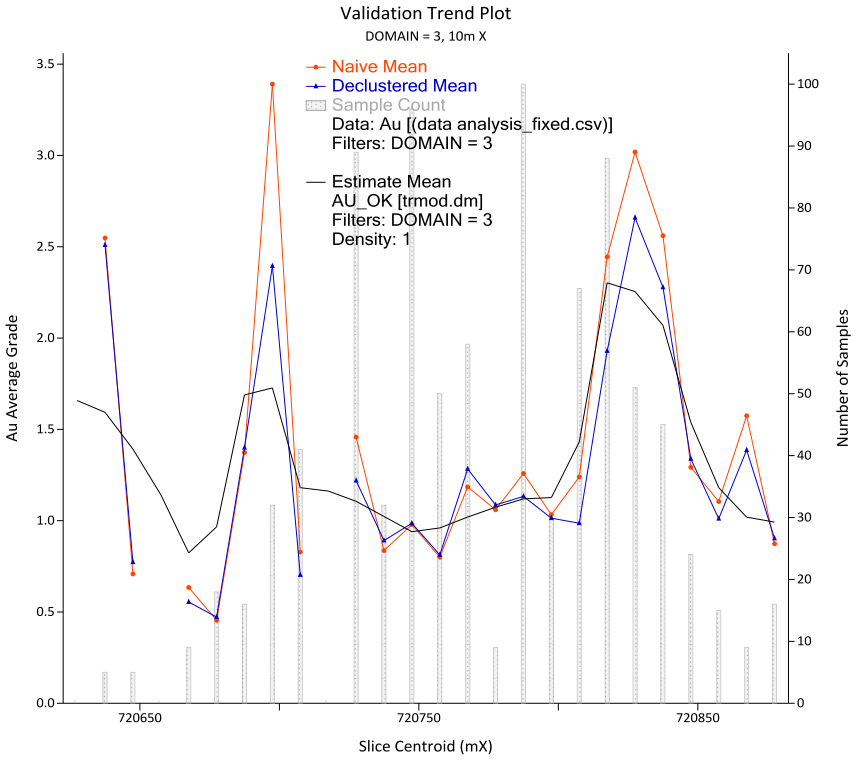
4.7.4 Global trend validation

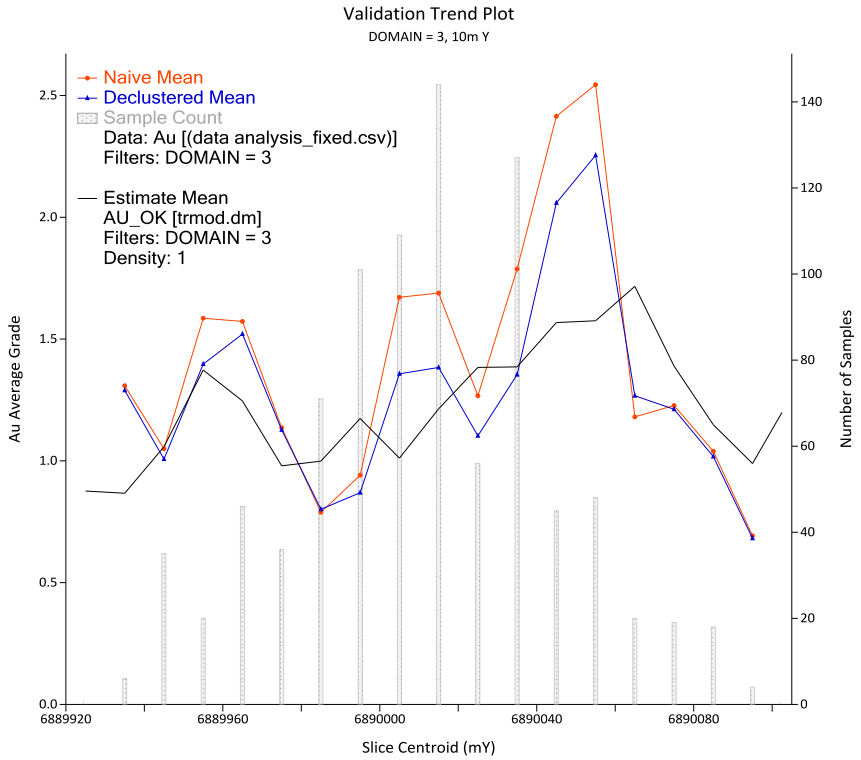
Trend plots should be created to compare the estimated grade to the input composites (declustered and top cut if necessary) for each estimation domain. These graphs compare the mean of the estimated grades to the mean of the input composite grades within a series of slices (easting, northing and elevation slices). It is important to select a slice interval that is appropriate to your block size and drillhole spacing so that the graphs are not over smoothed.

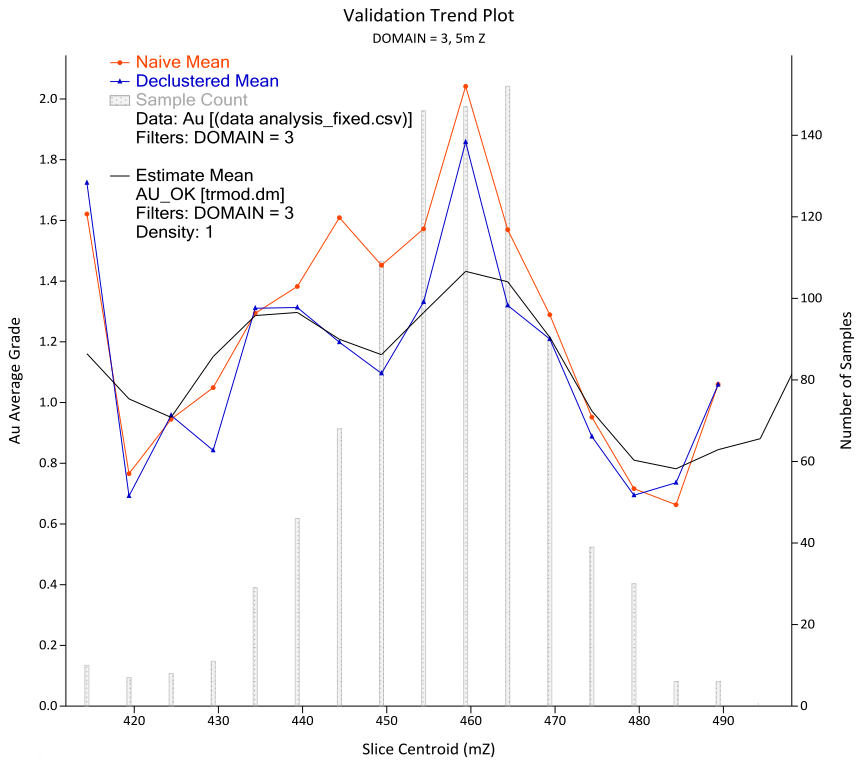
It is also useful to plot the total composite length or number of composites on the secondary axis of the graph to give an indication of the support for each slice.

The case study illustrated in Figure 4.55 shows trend plots in the easting (X), northing (Y) and vertical (Z) directions for a gold estimate. The graphs show that the model reflects the declustered input composites well in areas with good levels of data. The validation charts show the importance of declustering the input composite data, when required, particularly the chart in the Z direction which shows the naïve mean (red line) well above the model average (black line) through the central part of the chart. The reason that declustered input composites need to be used is because kriging has declustering 'inbuilt' into the equations by considering the position of each sample relative to each of the others. This is expressed in the left hand side of the kriging equations.

Figure 4.55 Case study showing trend plot validation with model grade (black), naïve composite grade (red) and declustered composite grade (blue)




Validation Trend Plot
DOMAIN = 3, 10m Y
Naive Mean
Declustered Mean
Sample Count
Data: Au [(data analysis_fixed.csv)]
Filters: DOMAIN = 3
Estimate Mean
AU_OK [trmod.dm]
Filters: DOMAIN = 3
Density: 1
Au Average Grade
Number of Samples
Slice Centroid (mY)
6889920
6889960
6890000
6890040
6890080


Validation Trend Plot
DOMAIN = 3, 5m Z
Naive Mean
Declustered Mean
Sample Count
Data: Au [(data analysis_fixed.csv)]
Filters: DOMAIN = 3
Estimate Mean
AU_OK [trmod.dm]
Filters: DOMAIN = 3
Density: 1
Au Average Grade
Number of Samples
Slice Centroid (mZ)
420
430
440
450
460
470
480
490

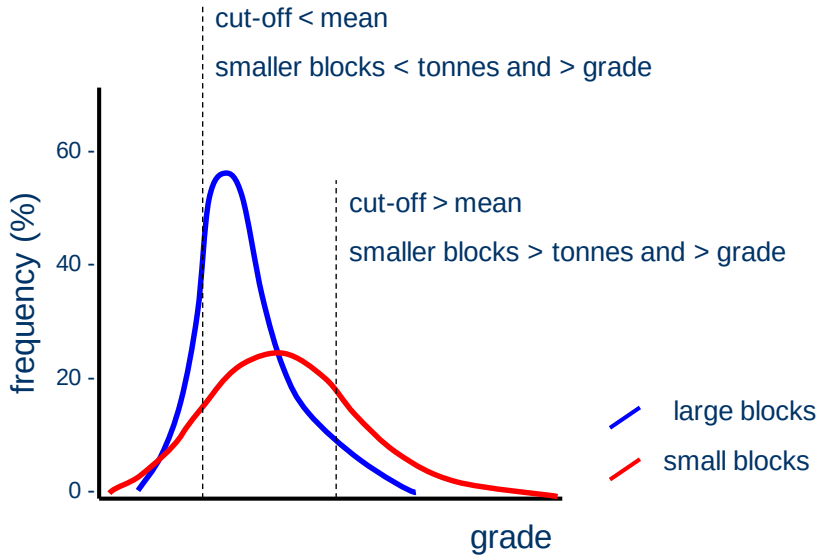
4.7.5 Global change of support

What is change of support

Resource estimates tend to be generated using block sizes which are larger than the anticipated mining selectivity (SMU). This is due to a lack of close spaced data and the requirement to minimise conditional bias in the resource estimate. The impact of larger blocks is reflected in a smoother, less variable estimate due to the volume variance effect.

The change in variability also impacts the grade tonnage relationship (Section 4.1). Smaller blocks result in more tonnes reported at a higher grade for cut-offs above the mean grade, and fewer tonnes reported at a higher grade for cut-offs below the mean grade. This changing grade tonnage relationship is illustrated in Figure 4.56 by the proportion under the distribution curve and above the cut-off grade.

Figure 4.56 Change in distribution and grade tonnage relationship with block size



The large resource estimate blocks are assumed to reflect an accurate estimate for a volume equivalent to the large block size. Accurate estimates at the SMU scale are not possible until closer grade control data is available.

Change of support is the process of adjusting a resource estimate for the volume variance effect so that it reflects the likely grade tonnage relationship at the anticipated SMU scale.

In addition, change of support can be used to adjust the variance of the input sample data so that it reflects the theoretical grade tonnage relationship for a particular block size. This process is called a theoretical global change of support. The resultant theoretical grade tonnage curve can be compared to the actual grade tonnage curve for a resource estimate (at the same block size), as a validation of the amount of smoothing incorporated into the resource estimate. In an ideal world, if there is no conditional bias in the resource estimate, the theoretical and actual grade tonnage curves will approximately match.

Mechanics of change of support

Change of support involves adjusting the distribution of the blocks, on a global or local scale, to reflect the anticipated variability of a different block size. The required adjustment can be calculated using the volume variance relationship where:

total variance = between block variance + within block variance

As the block size increases, the between block variance decreases and the within block variance increases (Section 4.1).

The required adjustment is a function of variability not grade. The variogram model defines the expected variability at any distance and can be used to calculate the within block variance for any block size[5]. Given the total variance (point variance or total sill), the between block variance can also be calculated for any block size. This information is used to rescale the distributions during change of support.

Global versus local change of support

Global change of support methods adjust the variability for the total domain. These methods take the total input distribution and stretch or contract it to give the output distribution.

Global change of support is used to report global grade tonnage results; it does not produce a locally accurate model.

Local change of support methods use the variability of the data within the local search ellipse to adjust the variability of the individual blocks in the resource estimate.

This provides an improved local accuracy; however, although the adjustment is applied to the local distribution, the adjustment factor applied is typically a global factor.

Change of support methods

Common methods for change of support include:

- Affine correction:
  - The affine correction is a global change of support which uses a direct distribution stretch approach that adjusts the variability of the block estimates to the variability of the SMU but maintains the shape of the block distribution. This method does not take into account the tendency for the distribution to become increasingly skewed with increasing selectivity (smaller blocks) and hence is only appropriate for normal distributions.
- Indirect lognormal correction:
  - The indirect log-normal correction is a global change of support similar to the affine correction but it takes into account the increasing skewness with increasing selectivity (smaller blocks). This is more appropriate for lognormal distributions.
- Discrete Gaussian change of support
  - The discrete Gaussian change of support is a global change of support which uses mathematical functions called Hermite polynomials to fit the input distribution and carries out the adjustment of the distribution in Gaussian space; meaning that the distribution is normal when adjusted. This method works for all types of distributions and is the method used for carrying out a theoretical global change of support for model validation.
- Uniform conditioning (UC):
  - UC is a global change of support which adjusts the variability of the blocks to the global data variability using a discrete Gaussian change of support. Although this is carried out on a block by block basis, it is a global adjustment and will not provide a locally accurate result.
  - UC is used to adjust global grade tonnage reports for anticipated selectivity.

[5] *Note the within block variance calculated by most mining software is sometimes referred to as the geostatistical f-factor. This is different to the variance adjustment f-factor commonly used in geostatistics.*

  - UC adds the most value when dealing with ‘difficult’ distributions (for example, not normally or log normally distributed). In most case studies it gives results that are very close to the actual production data.

- Indicator kriging (IK):
  - A local change of support can be carried out on an indicator kriged estimate to create a recoverable resource estimate. The indicator kriging process defines a CDF for each block. The change of support process uses a global adjustment and applies this locally to each block CDF.
  - Note that while this method is locally applied, it does not provide true local accuracy as the adjustment is based on global distributions. It does not take into account the fact that the adjustment required may vary locally.
- Conditional simulation:
  - Conditional simulation offers a more accurate reflection of the change in volume variance relationship between the large blocks and the SMU; however, there is still no greater accuracy of local estimates.
  - The conditional simulation approach involves running several conditional simulation models on a fine grid and reblocking each simulation to both the resource estimate block size and the SMU size. The reblocked simulations are then reported and a percentage change in tonnes, grade and metal calculated.
  - The percentage change is used as the adjustment factor for applying a change of support to the actual resource estimate.
  - Note that this change of support uses a global adjustment that is applied locally, as with UC.

Uses of change of support

Change of support can be used for applying a theoretical global change of support to sample data to provide an indication of the expected grade tonnage relationship at the block size being estimated. This is often used as a validation tool to confirm that the resource estimate is not over or under smoothed.

In addition, change of support can be used for:

- Adjusting global grade tonnage reports using a global change of support to reflect the anticipated mining selectivity.
- Creating recoverable resource estimates using a local change of support so that grade and tonnes above cut-off are available at the anticipated mining selectivity. Recoverable resource estimates can be used for mine planning purposes.
- Adjusting a resource estimate for the volume variance effect to allow reconciliation with grade control and production.

4.7.6 Other statistical validations

In addition to the standard four point validation described above, statistical checks can be carried out to determine whether there are any negative grades or unestimated blocks in the model.

The quantity and treatment of any negative grade estimates should be documented (‘Kriging weight anomalies’ in Section 4.4.5).

The treatment of unestimated blocks also needs to be considered. These can occur either due to insufficient data or waste domains which are purposefully not estimated. The treatment will depend on the ultimate use to which the model will be put. It the model is intended as a tool for mine planning and/or pit optimisation, missing estimates may not be allowed. The options for populating these blocks include:

- Rerun the estimate with an additional, more relaxed search neighbourhood.
- Run a nearest neighbour estimate using the existing estimated grades as the input data.
- Assign the average of the estimation domain.
- Assign default grades.

Blocks populated in this way should be flagged.

4.8 Classification and reporting

Public reporting of Mineral Resources requires that the resource estimate be reported to a relevant reporting code.

Guidelines are provided in these reporting codes for resource classification which communicates the perceived risk in the resource estimate to the investor (Snowden 2001, Edwards 2001).

This section deals with an overview of the various reporting codes, together with practical guidelines and tools for classifying and reporting a resource estimate.

4.8.1 Reporting codes

Several reporting codes have been developed around the world for the public reporting of Mineral Resources. These codes have been adopted as mandatory requirements by many professional organisations, stock exchanges and government regulatory bodies.

The codes provide a minimum standard for reporting, not a best practice guide to resource estimation. However, they do provide guidelines on items to take into consideration during preparation of a resource estimate.

The Committee for Mineral Reserves International Reporting Standards (CRIRSCO) released an International Reporting Template in 2006. This template is embodied in the current reporting codes for:

- Australasia.
- South Africa.
- Canada.
- USA (not endorsed by the SEC).
- UK, Europe and Ireland.
- Chile.
- Russia.
- Peru.

There are no material differences between these reporting codes; however, the Canadian code tends to be more prescriptive than the others.

Figure 4.57 and Table 4.3 summarise the main reporting codes, and professional organisations associated with these codes.

Figure 4.57 Reporting codes

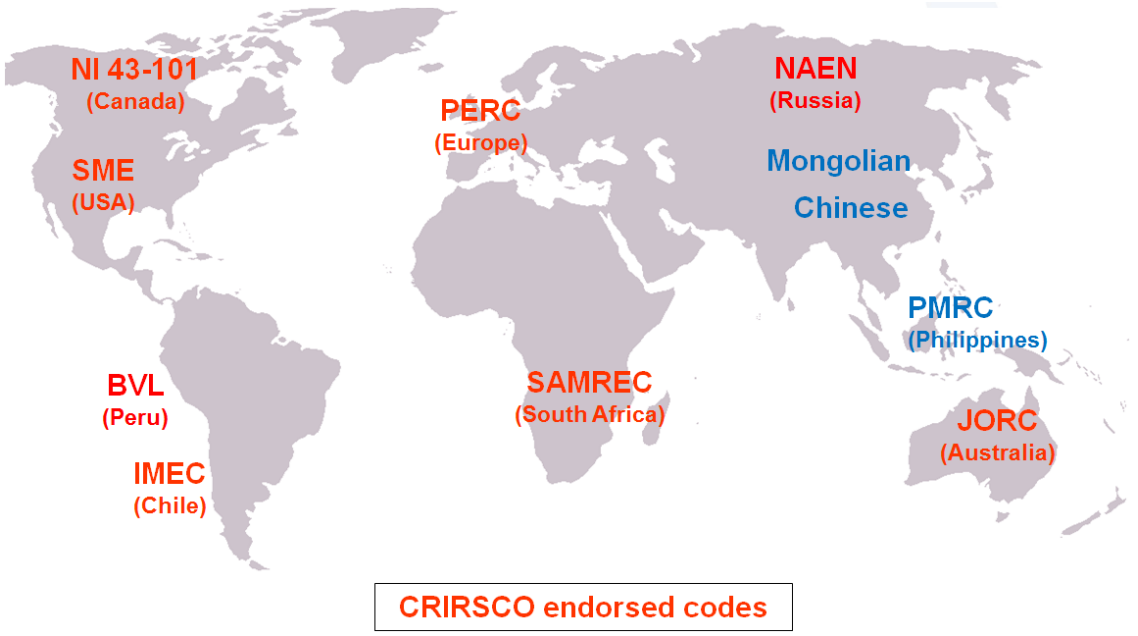


Table 4.3 National and international reporting codes and associations

Region	Code	Professional organisation		Comments
Australasia	The Australasian Code for Reporting of Exploration Results, Mineral Resources and Ore Reserves - 2004 "The JORC Code"	AusIMM AIG	Australasian Institute of Mining and Metallurgy Australian Institute of Geoscientists	Last update in 2012
South Africa	The South African Code for the Reporting of Exploration Results, Mineral Resources and Mineral Reserves – 2007 "The SAMREC Code"	SAIMM GSSA SACNASP ESSA PLATO	Southern African Institute of Mining and Metallurgy Geological Society of South Africa South African Council for Natural Scientific Professions Engineering Society of South Africa South African Council for Professional Land Surveyors and Technical Surveyors	CRIRSCO endorsed
Canada	CIM Standards on Mineral Resources and Reserves – Definitions and Guidelines – 2005 "CIM Definition Standards"	CIM	Canadian Institute of Mining and Metallurgy and Petroleum	CRIRSCO endorsed Used with National Instrument 43-101 ("NI43-101") and best practice guidelines

Region	Code	Professional organisation		Comments
UK, Ireland and Europe	The Pan-European Code for Reporting of Exploration Results, Mineral Resources and Reserves – 2008 "The PERC Reporting Code"	IoM3 GSL EFG IGI	Institute of Material, Minerals and Mining Geological Society of London European Federation of Geologists Institute of Geologists of Ireland	CRIRSCO endorsed
Chile	Certification Code for Exploration Prospects, Mineral Resources and Ore Reserves – 2004 "The IMEC Reporting Code"	IIMCh	Institution of Mining Engineers of Chile	CRIRSCO endorsed Fully implemented 2008
USA	The SME Guide for Reporting Exploration Results, Mineral Resources and Mineral Reserves – 2007 "The 2007 SME Guide"	SME	The Society for Mining, Metallurgy, and Exploration	CRIRSCO endorsed Not recognised by the SEC Refer instead to Industry Guide 7
Russia	Russian Code for the Public Reporting of Exploration Results, Mineral Resources, Mineral Reserves – 2011 "NAEN Code"	OERN	The Society of Experts in Mineral Resources	CRIRSCO endorsed
	Classification of Reserves of Mineral Deposits and Prognostic Resources of Solid Minerals 2006			Previous Russian code still used internally
Mongolia				New code in progress – endorsed by CRIRSCO
Peru	Code for Reporting of Mineral Resources and Ore Reserves – 2003	CIP	The Institute of Engineers of Peru	CRIRSCO endorsed
Philippines	The Philippine Mineral Reporting Code for Reporting of Exploration Results, Mineral Resources and Ore Reserves – 2007 "The PMRC"	PSEM GSP SMEP	Philippine Society of Mining Engineers Geological Society of the Philippines Society of Metallurgical Engineers of the Philippines	Code broadly based on CRIRSCO but not an endorsed member
China	Solid Mineral Reserve Classification 1999			Not CRIRSCO based

The following discussions on classification and reporting are generalised around the CRIRSCO based reporting codes. Individual codes should be reviewed for details of local requirements.

Principles of the codes

The main principles of the reporting codes are:

- Transparency.
- Materiality.
- Competence.

The reader must be provided with all of the relevant information required to understand the report and to be able to make a reasoned and balanced judgement on the contents.

The reporting codes require a Competent Person or Qualified Person who is a member of a relevant professional organisation (for example AUSIMM, SAIMM or CIM) to supervise the classification of the resource estimate and compilation of the supporting documentation. Most codes also allow a member of a Relevant Overseas Professional Organisation (ROPO) to act as a Competent Person. The issue of signing off as a Competent Person is discussed further during project completion (Section 5.2).

4.8.2 Classification

A Mineral Resource is an estimate of tonnes and grade in a deposit that has reasonable prospects of eventual economic extraction. The location, quantity, grade, geological characteristics and continuity should be known, estimated or interpreted based on geological evidence and knowledge.

Mineral Resources are reported as Inferred, Indicated and Measured with increasing level of geological knowledge and confidence. The general criteria in the reporting codes for these classification levels are:

- Inferred:
  - Low level of confidence.
  - Information of limited or of uncertain quality.
  - Assumed geological and/or grade continuity.
- Indicated:
  - Reasonable level of confidence.
  - Information gathered using appropriate techniques.
  - Assumed geological and/or grade continuity.
- Measured:
  - High level of confidence.
  - Detailed and reliable information gathered using appropriate techniques.
  - Confirmed geological and grade continuity.
  - Any potential for variation would be unlikely to materially affect economic viability.

The reporting codes contain a table 1 which provides a checklist for the assessment and reporting of Mineral Resources. This is a useful guide for items to consider when classifying a resource estimate. The main items to consider are:

- Data quality.
- Geological control and continuity.
- Grade continuity.
- Estimation method and block size.

- Mining method and reporting period.

The following sections look at each of these items and discuss practical tools and techniques for classifying a resource estimate.

Data quality

Assessment of data quality should address:

- The appropriateness of the drilling, sampling and assaying methods.
- Database integrity.
- Whether acceptable levels of accuracy and precision have been established.

The tools for data quality assessment include sampling theory (minimising sampling error) and QAQC as discussed in Section 2.

As a rule of thumb, the lack of a robust QAQC system precludes any classification above Inferred. In the case of historical sampling which lacks QAQC, a program of resampling or twinning of drillholes (incorporating QAQC sampling) can be carried out to confirm the quality of the original results.

Don't forget density when assessing data quality. Density is a major risk item in terms of grade tonnage reporting and should be subjected to the same degree of validation and QAQC as the grade attributes. The confidence associated with the measurement method and quantity of density measurements must be assessed during classification.

Geological controls and continuity

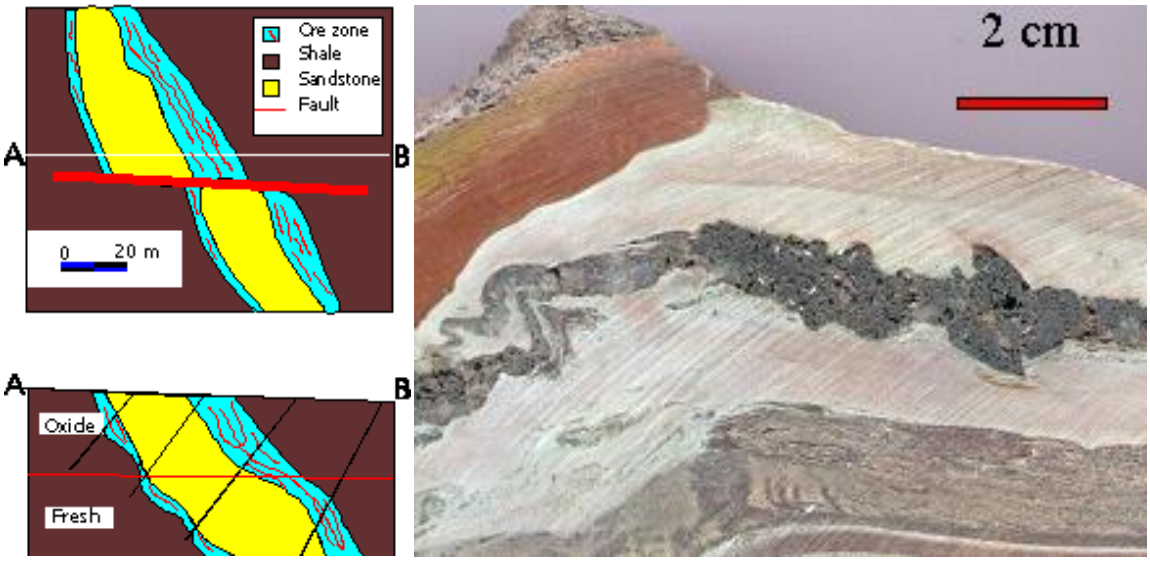
Assessment of geological control and continuity should address:

- The use of geology in guiding and controlling Mineral Resource estimation and the nature of any assumptions made.
- The impact of alternative interpretations.
- Any factors affecting geological continuity.

Geological mapping, logging and historical evidence can be used to confirm the geological controls on mineralisation and the geological continuity (Figure 4.58). Key questions include:

- Does mapping confirm the key mineralisation controls?
- What is the evidence of style and consistency?
- What is the extent of previous workings?
- Is the geology comparable with other known deposits?
- Does mapping indicate the potential for dislocation of or pinching out of the mineralisation?

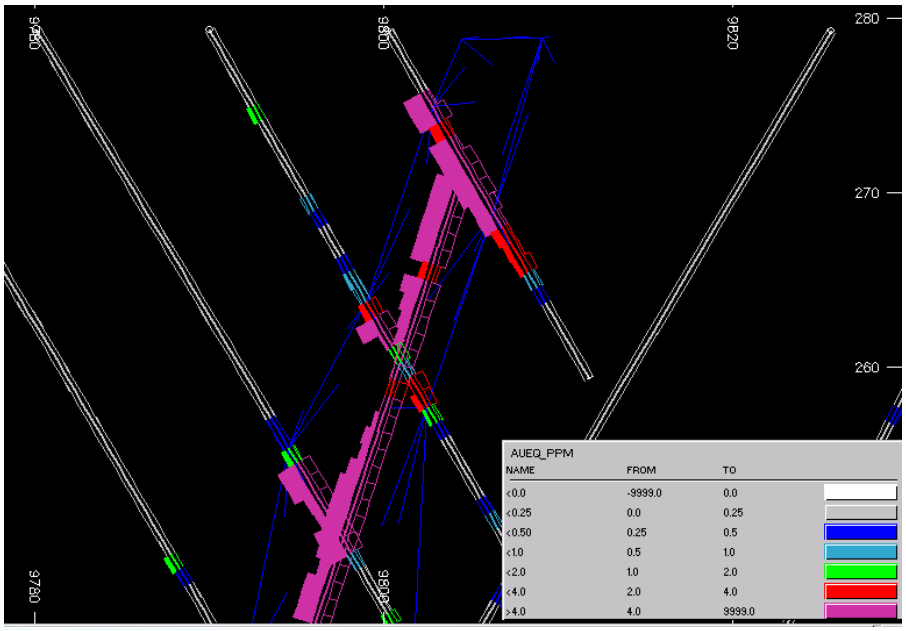
Figure 4.58 Geological mapping for confirming geological controls and continuity



The sensitivity of the interpretation can be tested by:

- Infill drilling to test the robustness and continuity of the interpretation.
- Scissor drillholes oriented down dip to the expected mineralisation to test the continuity and orientation of the interpretation (Figure 4.59). These drillholes need to be appropriately addressed during declustering (Section 3.3.4).
- Twinned drillholes to confirm existing mineralisation and geological logging
- Removal of drillholes and independent reinterpretation to test the impact.
- Alternative interpretations to test the impact on the tonnes, for example what happens if there are unidentified faults which pinch out the mineralisation (Section 3.1.2).

Figure 4.59 Scissor drillholes for confirming geological interpretation



Other factors which can potentially impact the interpretation include the introduction of biases due to:

- Sub-optimal drilling orientation.
- Mixed drilling types (reverse circulation versus diamond).
- Different drilling campaigns.
- Varying drilling depths.
- Several geologists responsible for logging.

These biases can be explored using Q-Q plots and comparing the statistics for the different data sources, constrained to a common volume.

Grade continuity

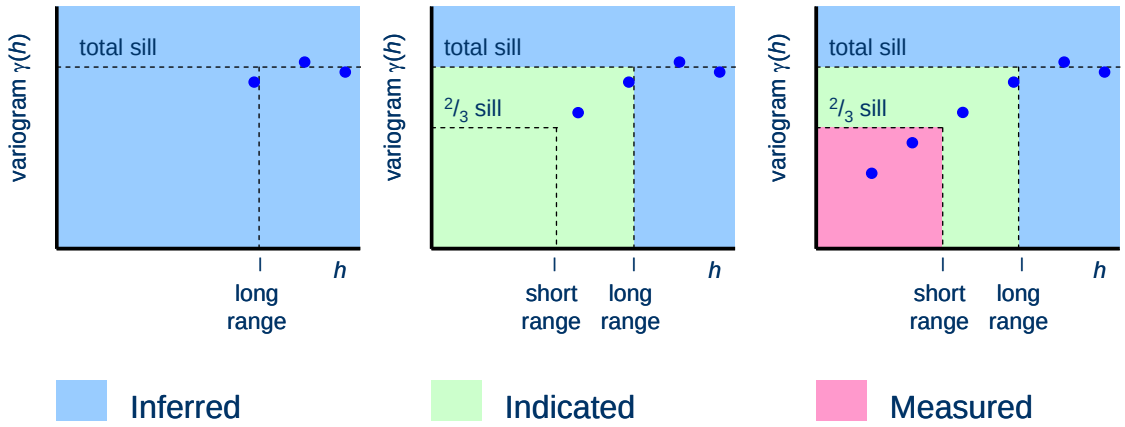
The main question when assessing grade continuity is whether the data spacing is close enough to demonstrate the continuity. This can be carried out by:

- Visual appraisal of grade continuity.
- Statistical analyses of distance at which grades are correlated.

The variogram provides a measure of the distance within which samples are correlated (Section 3.5) and can be used as a guide for classification based on grade continuity. The following provides a set of subjective guidelines to consider (Figure 4.60).

- When there is insufficient data to establish grade continuity, the resource should not be classified better than Inferred.
- When the data is sufficient to define the longer range grade continuity, but closer spaced data is required to define the shorter range grade continuity, then the areas of the resource informed by data closer spaced than the long range grade continuity could be classified as Indicated.
- When the drill spacing is sufficient to interpret at least two-thirds of the variability, then the area of the resource that is covered by data closer spaced than the range that corresponds to two-thirds of the sill, could be classified as Measured.

Figure 4.60 Using the variogram as a guide to classification



These guidelines assume all other criteria of the reporting codes are met and will require downgrading if there are risks in other areas.

Estimation method and block size

Essential elements to consider when assessing the nature and appropriateness of the estimation techniques include:

- The volume variance relationship and selectivity.
- Estimation methods and parameters including block size, search neighbourhood and discretisation.
- Validation and reconciliation.

The degree of smoothing is sensitive to the estimation method used to generate resource models. The resource estimate should be reported to a realistic degree of selectivity based on potential mining scenarios (open pit or underground; bulk mining or selective mining).

Estimation methods and parameters should be appropriate to the style of mineralisation. The conditional bias statistics used to optimise the estimation parameters can be used as an aid to quantifying the robustness of the estimate.

Kriging efficiency and slope of regression can be generated in the final estimate and used as an aid to classification. As a rule of thumb, a Measured classification should have better than 80% kriging efficiency and 0.9 slope of regression. This is a subjective analysis and will be dependent on the style of deposit.

Kriging variance can also be used, however, this is a relative number and hence there is no method of determining what value constitutes a robust estimate. If using kriging variance, the normal method is to select an area where there is known to be high confidence in the estimate and use this as a guide as to what kriging variances to apply.

Validation and reconciliation information should also be reviewed to determine whether there are any factors influencing the robustness of the estimate.

Mining method and reporting period

The important aspects to consider in terms of mining method and reporting period include:

- **Selectivity** – as discussed previously, the resource estimate should be reported to a realistic degree of selectivity based on the potential mining selectivity (SMU).
- **Accuracy and scale** – the accuracy of the resource estimate needs to be understood in terms of the reporting scale. Is it accurate at a local or global scale, and what is required for mine planning?
  - Globally accurate resource estimates may be suitable as conceptual estimates, or for long term planning. Locally accurate resource estimates are generally needed to provide sufficient information for short term planning and grade control.
- **Mining approach** – ultimately the degree of confidence depends on the mining approach (open pit versus underground, bulk versus selective, high versus low cut-off grades).
- **Potential for eventual economic extraction** – only areas that are potentially economic can be reported as a Mineral Resource. Many companies carry out mine optimisation on a resource estimate to define the limits to the area of potential economic extraction. For example a preliminary pit design or the outline of a potential underground bulk cave may be used to provide limits for the Mineral Resource. Any portion of the resource estimate outside of these limits should not be reported as a Mineral Resource.

Note that some reporting codes require a pre-feasibility study and mine design to be carried out prior to reporting a Mineral Resource.

Bringing it all together

Often classification methods focus on grade continuity and ignore other aspects which may introduce risk to the project. Final classification of a resource estimate should take into account all of the aspects discussed in the previous sections.

The main considerations and tools for classification include:

- Sampling theory and QAQC to assess the quality of the data.
- Mapping, check drilling, reinterpretation, and Q-Q plots to assess potential biases are used to achieve confidence in the geological controls and continuity.
- Variogram analysis and drillhole spacing to determine grade continuity.
- Kriging efficiency, slope of regression and kriging variance to assess estimation quality.
- Consider an appropriate level of selectivity, reporting period and area of potential economic extraction.

4.8.3 Resource reporting

Resource estimate reporting

Once the resource estimate is classified, resource reporting can be carried out. Resource estimates are usually reported by classification category for all attributes, at a series of cut-off grades. Grade tonnage curves can be created to illustrate the grade tonnage relationship.

If the resource estimate is an update of an existing resource estimate, both results should be shown and a discussion included on the reason for and degree of change.

Mineral Resource reporting

Final reporting of a Mineral Resource will be at a grade cut-off based on economic considerations. Assessment of the expected revenue minus the cost of producing the product gives a break even cut-off grade for mining. Other economical, mining and processing considerations are then used to determine the cut-off grade for reporting and mining.

Some companies report Mineral Resources based on metal equivalence rather than grade. In these instances the calculation, costs, recoveries and assumptions used to determine the metal equivalence, must be documented.

Mineral Resources should always be reported by classification category. Most of the reporting codes allow a total to be reported as long as the break down is also shown. However check the local reporting code as some codes require that Inferred Resources be separately reported and not included in any totals.

Note if working with multi-elements, the tendency is to consider the main economic attributes when defining classification. If some attributes have a higher level of risk attached to them, these attributes should not be reported in the final Mineral Resource. Additionally, non-economic attributes (for example contaminants) should not be reported as part of the Mineral Resource as they are not economically extractable.

5 Project completion

5.1 Report writing

There are 10 basic steps to putting together a report.

1. Get set:
   - Prepare the work area to be conducive to writing.
2. Grasp the reader's mindset:
   - Who is the audience? Ensure that the information in the report is relevant and pitched to the correct audience. This is particularly important when stepping from full technical documentation to a summary report which will be read by management.
3. Identify the main message:
   - What is the focus for the report? Is it reporting a Mineral Resource estimate for public reporting or an update of an internal resource estimate for mine planning? Is the focus the final classified resource estimate or is the reader more interested in the changes since the last update?
4. Do your research:
   - Collect and organise all relevant facts, files, information and references.
5. Prepare:
   - Think about what needs documented. Develop a process flow for the work to be documented. Techniques such as brainstorming, mind mapping or free writing can be useful aids to this process.
6. Table of contents:
   - The contents table should be set out in a logical sequence. A standard contents table will include the following items:
     - Title page.
     - Table of contents.
     - Executive summary.
     - Introduction.
     - Main content.
     - Conclusions and recommendations.
     - References.
     - Appendices.
   - For the main content section of a technical resource estimation report, the process flow chart provides a good starting point for setting up the table of contents.

7. Write first draft:
   - Put together a first draft for the main content and introduction. The introduction should introduce the aim of the report and reason for carrying out the work.
   - The main content of the report should include documentation on each stage of the resource estimation process. Section 7.1 provides a list of recommended items to be included.
   - Ideally a technical report should provide sufficient information for the reader to recreate the resource estimate, given the input files. For summary reports the emphasis should be on the reporting code's principles of transparency and materiality. What is relevant to the reader? What could potentially impact the results? Document all decisions and uncertainties related to the process.
   - Keep the report concise and to the point. Where possible use the simplest wording to get the information across.
8. Conclusions, recommendations and executive summary:
   - These are the most important parts of any report and should be written after the bulk of the report has been completed so that all available information is collated.
   - Conclusions should emphasise what the end result was. What is the important information that this work resulted in? Any outstanding work, problems or risks should also be discussed.
   - Recommendations should provide the reader with a way forward. How can the process or results be improved on? What is required to complete outstanding work or mitigate risks?
   - The executive summary should provide the results of the work together with a summary of all material aspects of the process. An emphasis should be placed on any risks or problems that may impact the results.
   - Put the answer at the start of the summary not the end. The reader wants to know the result as soon as they open the report. Most reports are never read from cover to cover and most decision makers only read the summary.
9. Editing and review:
   - Always edit a report before handing it over. Common issues include spelling, grammar, formatting, cross references, consistency of tense and consistency of abbreviation use.
   - Make sure all graphics are of high quality and include all relevant information, for example legend, scale and north arrow on drillhole plans.
   - All references should be documented at this stage. Ensure that all material is correctly referenced. Note that permissions may be required for the use of external material or quotes or to name sources, particularly for public reports.
   - All reports should be peer reviewed before finalisation to check for technical and editorial issues.

10. Presentation and delivery:
    - First impressions will be impacted by report presentation and readability. The reader needs to be able to clearly understand the message being delivered.
    - For internal technical documentation it is good practice to include a CD or DVD of all main files in the back of the report or a list of files in an appendix with a network location.
    - In addition, all relevant files should be backed up and archived with the report to facilitate auditing and future use.

Tips

- Once the contents table is set up it is not necessary to write the report from start to finish. If writers block is an issue try starting with the easy parts and move around the report to fill in the blanks.
- If the report is an update, use the previous one as a template to speed the process up.
- Keep notes during the resource estimation process so that no information is missed and no rework is required at the documentation stage.
- If possible write notes directly into the report.
- Make graphics of report standard as you go. Don't leave them to the end or create poor quality ones as this will require rework.

5.2 Sign off

Reporting a Mineral Resource to a reporting code standard is not a guarantee that the report is correct.

The reporting codes require a Competent Person (or Qualified Person for CIM) to sign off on all public reports, including Mineral Resources. By acting as the Competent Person and signing off on a public report you are personally taking responsibility that the information is correct.

A Competent Person is defined as someone who has:

- Appropriate professional membership, for example AusIMM, SAIMM, CIM or Recognised Overseas Professional Organisation (ROPO).
- 5 years' experience which is relevant to the style of mineralisation, type of deposit and process being undertaken.

It is possible for several people to act as Competent Persons for different aspects of one project.

The main role of the Competent Person is the preparation or supervision of preparation of supporting documentation for public reporting. The Competent Person may be an auditor or reviewer as opposed to the person carrying out the actual resource estimate.

Public reports are designed to inform investors and advisors. They are the responsibility of the company; however, they must be based on the information and supporting documentation provided by the Competent Person. In addition, the company must obtain written permission from the Competent Person prior to releasing a public report.

If things go wrong there is the potential for legal liability if negligence can be determined. Issues can be avoided by ensuring that all decisions and potential risks are well documented and the work has been carried out in a professional manner using the best information available at the time.

5.3 External auditing

External auditing of resource estimates is standard practice for many companies and should not be treated as a criticism of ability. Audits may also be instigated by financial institutions during the funding stage to assess the level of risk in a project.

There are several levels of auditing from a high level review through to a detailed technical due diligence. High level reviews can include:

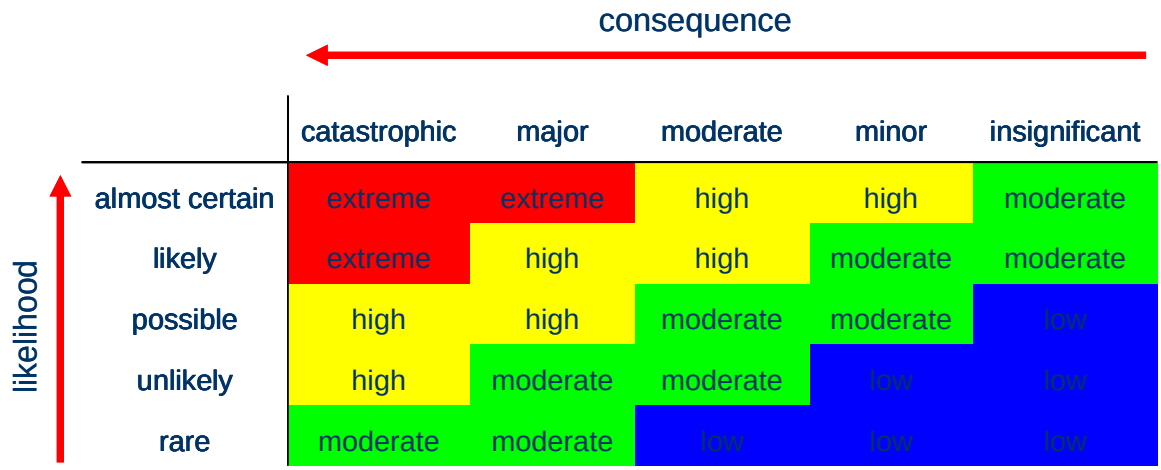
- Review of the resource estimate report.
- Independent validation of the resource estimate against the input data.
- Validation of the Mineral Resource reporting.

This level of audit is looking for fatal flaws or major risks which could impact on the value of the project. If an area of risk is identified, a more detailed drill down of this aspect may be carried out. High levels reviews generally take from two days to a week and result in a short memorandum or report outlining the findings together with recommendations for improving the process and mitigating any risks.

A full technical due diligence involves independent validation and review of all aspects of the project. For the resource side of things this will include everything from drilling and sampling through to the final Mineral Resource. Independent sampling may also be required to confirm the mineralisation.

This level of audit can take several weeks to complete. It is designed to confirm the technical integrity of the input to the financial model and to identify all risks. Risks are categorised by the consequence and the probability of occurrence (Figure 5.1).

Figure 5.1 Risk assessment matrix



A comprehensive technical report will be prepared discussing all risks at each stage of the process with recommendations for improving the process and mitigating the risks.

While audits are designed to identify any fatal flaws, there is no guarantee attached to this unless the auditor has signed off on the Mineral Resource (or aspect of the project audited) as a Competent Person.

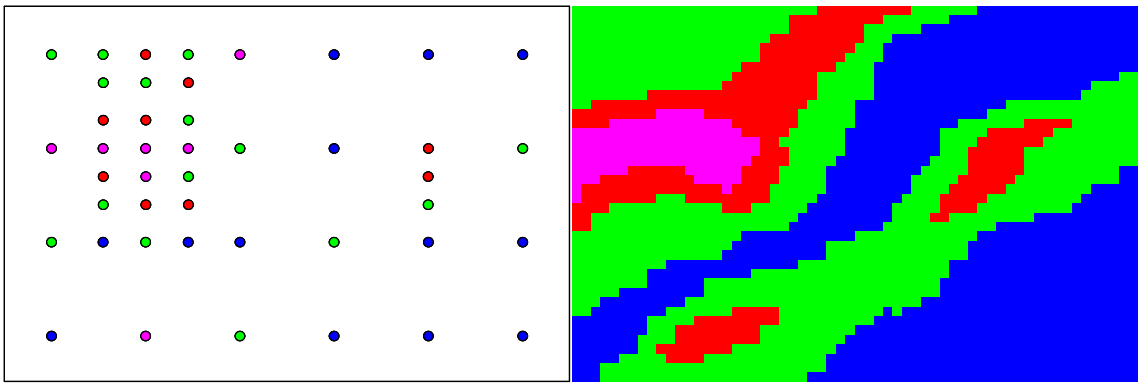
6 An introduction to conditional simulation

Grade simulation is becoming more common as an alternative or as a support to producing kriged estimates for resource estimation. The main differences between kriged estimates and simulations are:

- There are always a large number of simulations, typically 50 to 100 simulations, sometimes more.
- Simulations are not as smooth as kriged estimates.

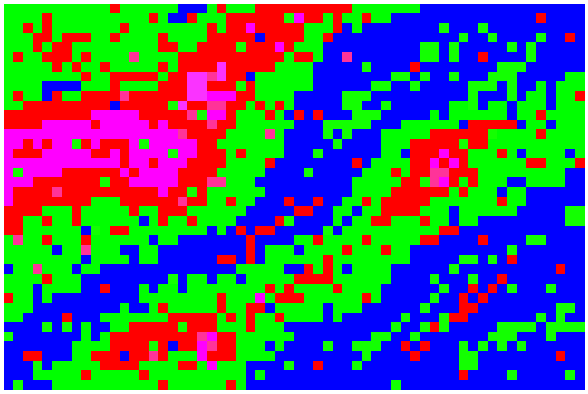
Kriging aims to produce a “best” case estimate which minimises estimation error and results in a smooth “average” grade model. This means that the true degree of grade variability is not reproduced (Figure 6.1).

Figure 6.1 Input sample data and kriged estimated grades showing smoothing



Simulation aims to reproduce the degree of grade variability as well as the overall grade distribution. The result of this is that the grade of a block for an individual simulation has a high degree of error. By creating multiple simulations, the probability of a block being above cut-off can be determined. Figure 6.2 illustrates this variability for one simulation of the input sample data.

Figure 6.2 Simulated grades showing variability



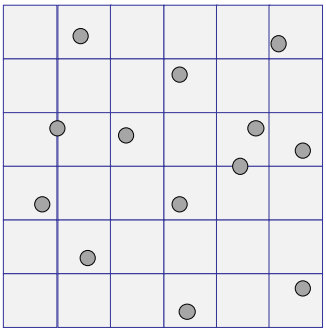
There are several methods of grade simulation including:

- Turning bands.
- Sequential Gaussian conditional simulation (SGS).
- Sequential indicator conditional simulation (SIS).

Simulations are termed “conditional” as the grades in the simulation are “conditioned to” or based on the grades in the drillholes surrounding the blocks. The methodology for SGS and SIS is as follows:

Step 1

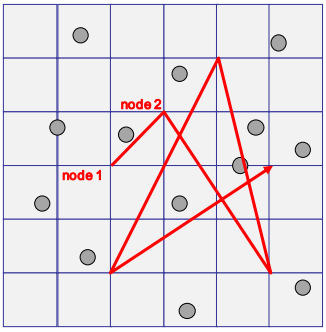
Set up a dense grid of nodes over the area of interest



sample location

Step 2

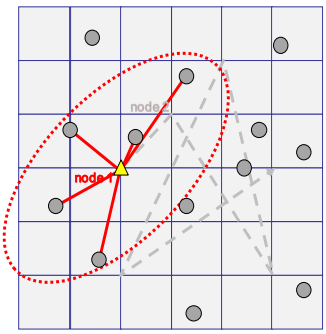
Set up a random path to visit each node once



sample location

Step 3

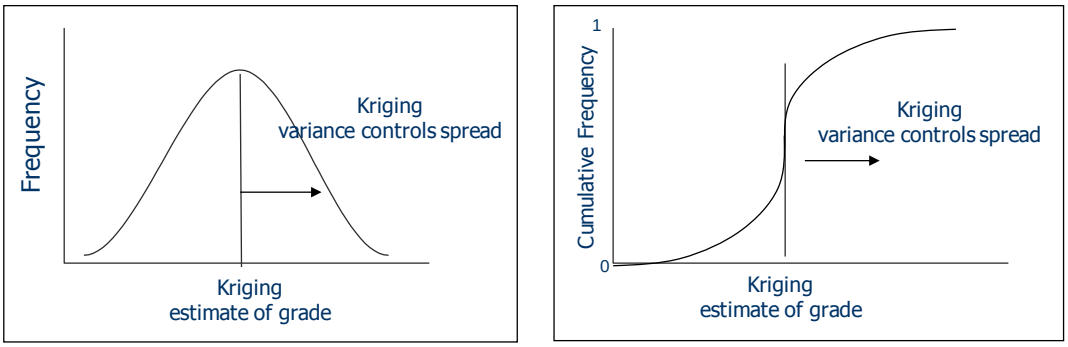
Krige the first node using ordinary or simple kriging of Gaussian data for SGS and indicator kriging for SIS.



sample location

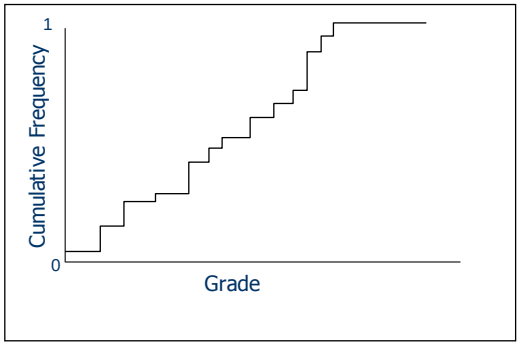
Step 4 SGS

Create a CDF for the node using the estimated mean and kriging variance. SGS kriges using Gaussian data which has a symmetrical distribution, therefore the estimated mean approximates the mean of the normal distribution and the kriging variance approximates the variance of the normal distribution.



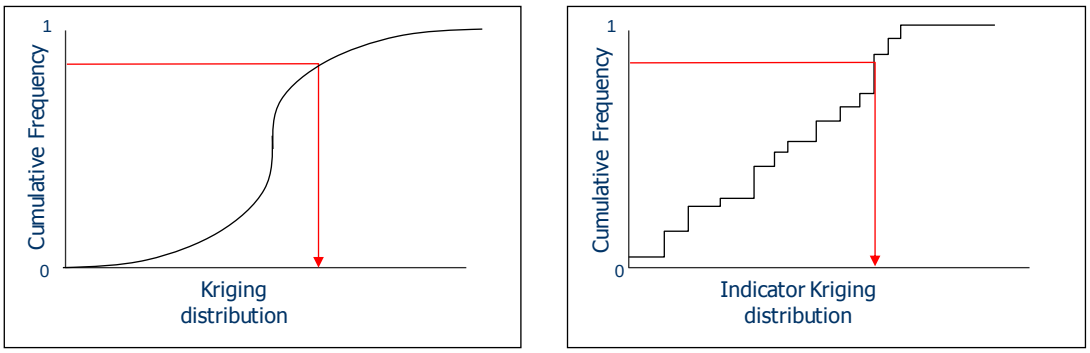
Step 4 SIS

Create a CDF for the node using the estimated probability of the grade being below each indicator threshold.



Step 5

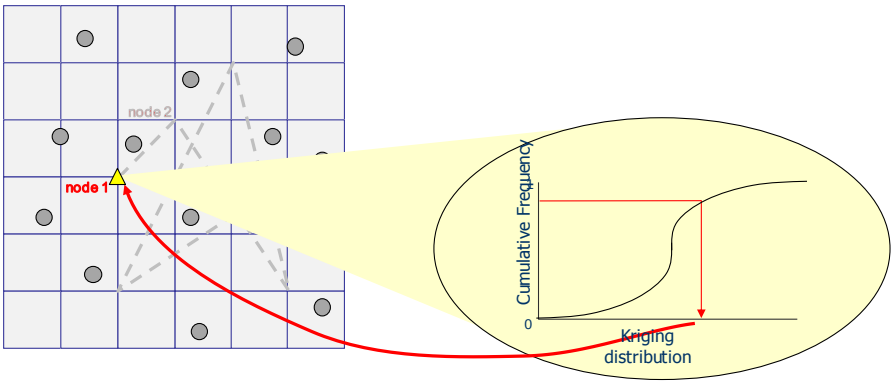
Randomly sample the CDF using a Monte Carlo simulation. This is basically a random number generated between 0 and 1 to select the frequency on the CDF.



SGS SIS

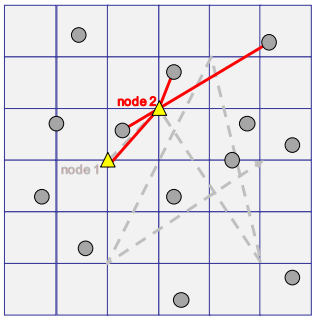
Step 6

Set the simulated value at node 1 to the Monte Carlo sample value.



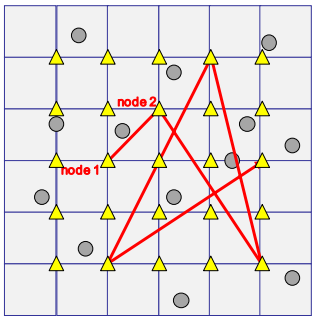
Step 7

Move to the next node and repeat using the original sample data and the previously simulated nodes.



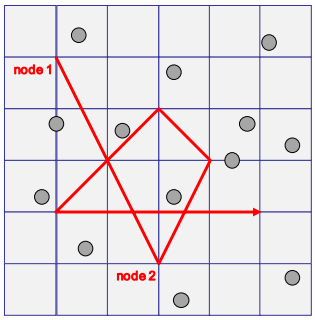
Step 8

Repeat until all nodes are simulated.



Step 9

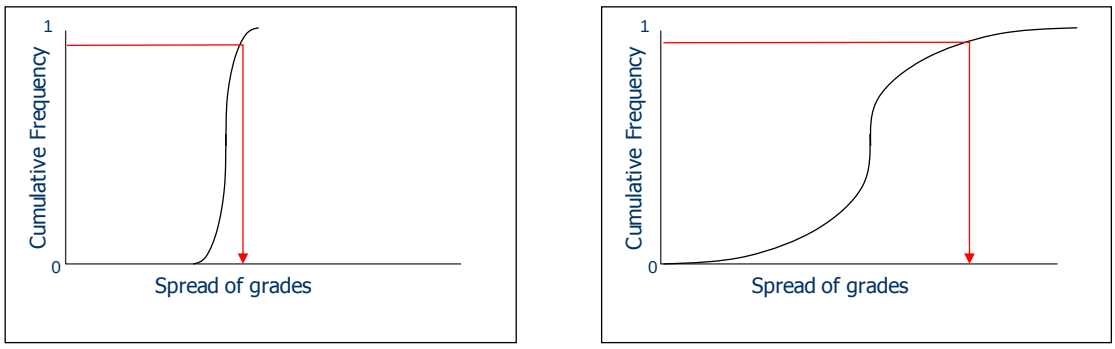
Start the next simulation using the original data and a new random path.



The variability that is incorporated in the simulations depends on the spread of the CDF (Figure 6.3). In SGS this is a factor of the kriging variance and hence is a factor of the variogram and the data spacing. SGS assumes strict stationarity in the data as it uses simple kriging. This means that the mean and variance should be consistent across a domain. Ordinary kriging can be used in the absence of strict stationarity but will not work well unless there is dense sample data.

For SIS the variability is based on the estimation of probability at each indicator threshold and hence is a factor of the variogram and the local grade variability. If the variability changes across a domain then SIS is more suitable as it will account for this change.

Figure 6.3 CDF for grade selection in low and high grade variability domains



CDF in low grade variability domain

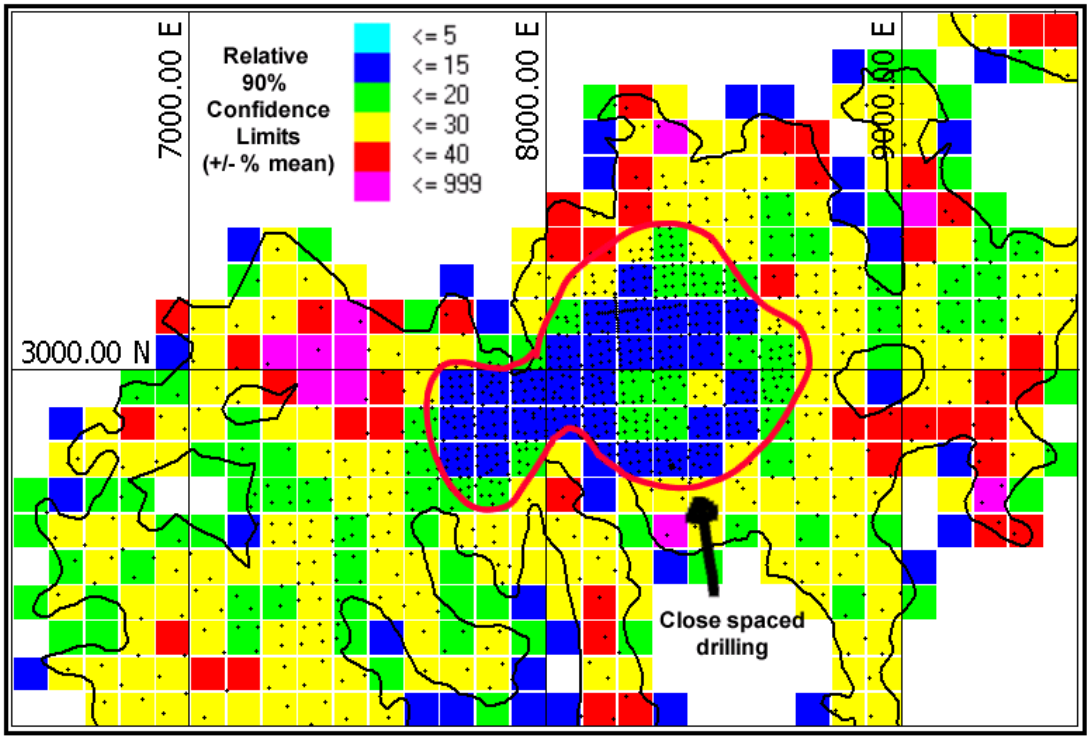
CDF in high grade variability domain

Running a large number of simulations provides a measure of risk by defining how much the grade can change at each location in the resource estimate. This makes simulations useful in many areas including:

Classification

Resource estimates can be classified according to the grade variability seen in the simulations rather than purely based on drillhole spacing. The grade variability may show that there are areas of the resource estimate that have close spaced drilling, but have a high degree of grade variability and therefore a high degree of uncertainty in the estimated grades. Other areas of the resource estimate may have wider spaced drilling with less variability in grade and therefore a higher degree of confidence in the estimated grades. Figure 6.4 illustrates grade variability based on conditional simulation with respect to drillhole spacing. In this instance there are areas of increased grade variability within the close spaced drilling area.

Figure 6.4 Case study showing grade variability based on conditional simulation compared to drillhole spacing



Testing designs

Simulations can be used to test the risk associated with mine plans such as:

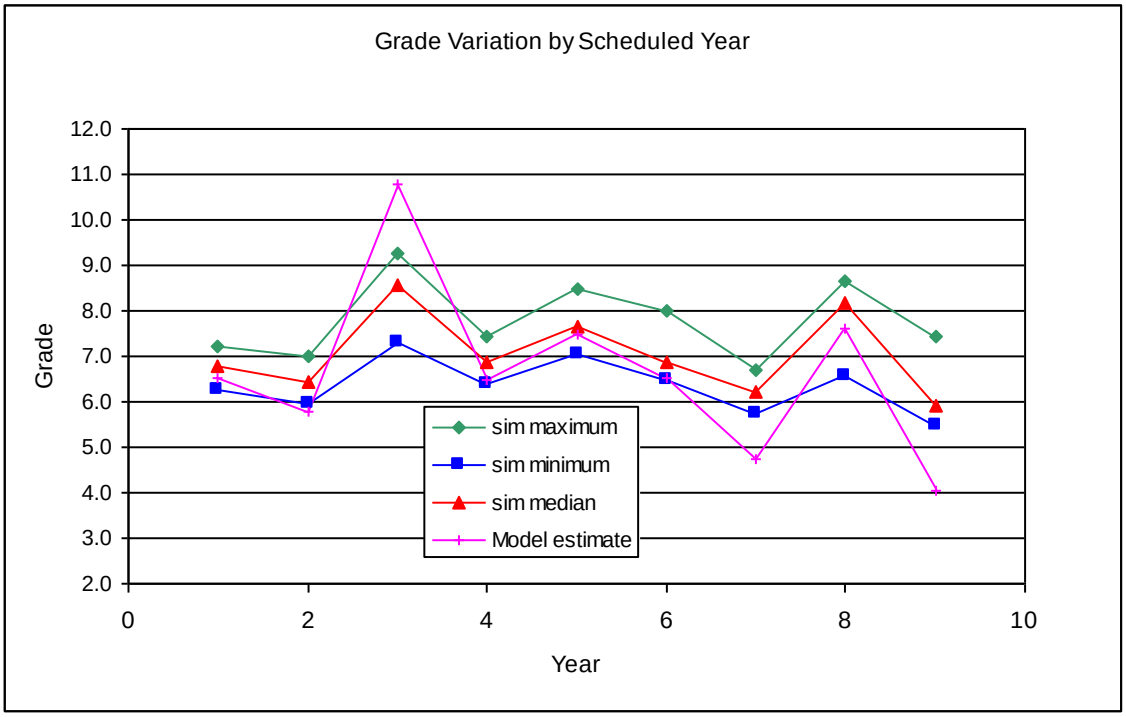
- Pit designs.
- Mining schedules.
- Stope designs.
- Variability in mill feed.

As each simulation is different, reporting several simulations within a fixed volume will give different grade and tonnage information above cut-off. This information can be used to test how optimal a design is or how sensitive cost and financial decisions are to variations in grade.

As an example, pit designs could be assessed using the average, 95th percentile and 5th percentile simulations (90% confidence limits) to define areas of uncertainty which may require additional drilling.

By reporting simulations by scheduled period, risk can be quantified over time and periods of higher risk flagged. Figure 6.5 graphs the range of simulated grades for an annual schedule against the resource estimate grades. This provides two pieces of information; the expected variation in grade for each year from the range of simulations, and the uncertainty in the resource estimate which is being used for mine planning based on a comparison of the resource estimate and the simulation results. There is a high risk in year 3 as the resource estimate is reporting higher grade than any of the simulations. This could provide a target for additional drilling or review.

Figure 6.5 Case study using simulations for schedule risk



Simulation resource models

Simulations can be used to generate a resource model. A single simulation cannot be used by itself due to the high degree of local error for each block; however, this local error can be reduced through probability weighted averaging all of the simulated values for each block to give an "E-Type" model. Averaging simulations gives a single grade per block which will look broadly similar to an ordinary kriged resource estimate.

Alternatively a recoverable resource model similar to those produced through indicator kriging or uniform conditioning can be generated from simulations. With simulation, blocks above cut-off are counted to generate the probability above cut-off rather than using a change of support technique.

Geological or rock property simulation

For some styles of mineralisation, physical properties or mineralised rock types can be simulated. These simulations can be used to test interpretations, sensitivities to domaining, or tonnages of favourable rock types.

Some simulation methods employed for this include:

- Categorical indicator simulation
- Truncated Gaussian simulation

- Plurigaussian simulation
- Fluvial simulation
- Simulated annealing.

‘An Introduction to Applied Geostatistics’ (Isaaks and Srivastava, 1989) is a good starting point for further reading on conditional simulation.

7 Appendices

7.1 Documentation

This list is provided as a guide to technical documentation for resource estimation. More or less information may be required dependant on the end use of the report and local requirements.

7.1.1 Informing data

Database integrity

- Cut-off date of the database and file names.
- Location plot of drillholes.
- Number of drillholes and hole types. If updating an existing resource estimate then state the number of additional drillholes since last time.
- Assay fields and methodology.
- Comment on any historic data. This is important for operations with a detailed history as there may be less confidence in some data. Define historical assaying methods and detection limits. Note if any of this data was excluded from previous estimates and why.
- Any excluded drillholes and the reasons.
- Geology fields and codes for use in the estimate.
- Treatment of below detection and missing values.
- All validation changes and issues.
- Discussion of risks associated with data.
- It is recommended that a random audit of 5 to 10% of the database is undertaken by cross checking the hard copy data against the database. Document the results in terms of percentage errors.

Data quality

- Details of QAQC procedures.
- Assessment of the representivity of QAQC data.
- Analysis of duplicates and assessment of precision.
- Analysis of standard sample results.
- Blanks analysis and assessment of contamination during sample preparation.
- Any QAQC issues and documentation of any corrections to data.
- Discussion of the risks associated with the quality of the assay data

Many companies carry out routine QAQC analysis and documentation (for example, monthly reporting). In these instances a summary of the results for the relevant drilling programs or period of time can be included in the resource documentation, and the detailed QAQC report referenced. It is important to comment on any issues which could impact on the confidence in the data.

7.1.2 Data analysis

Geological interpretation

- Summary of regional and local geological model.
- Criteria used to interpret each geological control.

- Confidence associated with the interpretation and the impact of any alternate interpretations on the tonnage and continuity.
- Degree of extrapolation between and beyond drillhole data.
- Drillhole orientation with respect to the true width of the mineralisation. This is to prevent optimistic reporting of results with drillholes orientated down dip of the mineralisation. For resource estimation the ideal orientation is perpendicular to the mineralisation.

Coding and compositing data

- A table of all codes used.
- The composite interval length including reasons for selecting this interval.
- Describe the compositing methodology.
- Validation results.

Statistical analysis and domaining

- Domain description including:
  - Criteria used to define each domain.
  - Domain validation results.
  - The boundary type for each domain and evidence for your selection.
- Tabulation of summary statistics of composited data for each domain (declustered if appropriate).
- Histograms and probability plots for each domain (declustered if appropriate).
- Discussion of grade population characteristics within each domain.
- Scatterplots and correlation tabulations if working with multiple attributes
- Q-Q plots and/or box and whisker plots comparing different data sources.
- Declustering issues, method used and test results. Note if declustering has an impact on the statistics then declustered statistics should be presented. Raw composited statistics may be included in the appendices.

Top cutting strategies

- Top cuts applied to each domain and method of selection.
- Number of samples top cut.
- Top cut mean, standard deviation and coefficient of variation to show the impact of the top cuts.

Spatial analysis

- Discussion on types of variograms used, parameters and tolerances.
- Discussion on directional analysis and relationship with geological model. Include variogram fan diagrams if relevant.
- Figures illustrating final variogram models for each estimation domain.
- Tabulations of the final variogram directions and model parameters.
- Back-transformed variogram model parameters if applicable.
- Mining software specific parameter files including rotations should be included in an appendix.

7.1.3 Resource estimation

Optimising parameters

- Spatial location of optimisation tests with respect to mineralisation domains and drillhole spacing.
- Details of all scenarios tested.
- Parameters used for testing including variogram parameters and any parameters set as defaults during the tests.
- Graphical representation of parameter optimisation results.
- Discussion on results.

Building the block model

- Discussion on block size selected.
- A description of the block model construction process.
- Block model prototype details including origin, block size, extent and number of blocks.
- Subcell usage including minimum subcell size.
- A table of all codes used.
- Validation results.

Search neighbourhood parameters

- Tabulation of search parameters for each estimation domain.
- Discussion on search orientations with respect to the geological model and variography.
- Discussion on search parameters selected.
- Mining software specific parameter files including rotations should be included in an appendix.

Estimation

- Discussion on estimation method.
- Attributes estimated.
- Estimation parameters. Mining software specific estimation parameter files should be included in an appendix.
- Comment on unestimated or negative grades and their treatment

Density modelling

- Methods of density measurement. If multiple methods have been used then comment on the quantity and confidence in the various methods.
- Method used to populate block model with density.

Validation

- Example sections illustrating estimated grades and drillhole composites.
- Tabulation showing global mean grade validation for each estimation domain.
- Histograms comparing population distributions for estimated grades and input composites.
- Global trend plots in relevant orientations for each estimation domain.
- Discussion on any issues arising from the validation.

Classification and reporting

- Reporting code used for classification.
- Classification levels assigned to the resource estimate and the basis for these.
- Information on all material items with reference to the checklist table in the reporting code. Ideally include a table with comments on each check list item.
- Example illustrating the classification.
- Details of any cut-offs or constraints used for reporting and the basis for these. If metal equivalence calculations are used then the calculation, costs, recoveries and assumptions should be detailed.
- Grade tonnage curves and tabulation of the resource estimate reporting at a series of cut-offs for each level of classification.
- Comparisons to previous resource estimate if relevant, with discussion on degree of and reasons for change.
- Final Mineral Resource tabulation.
- Details of the Competent Person (if using a certificate this can be included as an appendix).

7.2 Data validation check list

Collar and survey validation

- Table relationships – do all surveys have collars and do all collars have surveys?
- Drillhole identifier consistency – check for consistency in case; check for blanks or errors.
- Duplicate data – are there duplicate collar or survey records, or duplicate collar locations?
- Spatial validation – look at the data in three dimensions and check that it is all there and that it is located in the right place.
- Topography – what is the basis of and expected accuracy of the topography? Has vegetation, excavations and filling been excluded from the surface topography interpretation (common issue for coal and mineral sands)?
- Collar elevations – check collars versus topography. What is the expected accuracy of the topography and the survey data?
- Planned versus surveyed collars – are there any planned coordinates in the data? If so are they planned or just not surveyed? If any elevations are set arbitrarily then topography can be used to reset them.
- Survey method should be specified. Is it planned coordinates, collar survey only or downhole surveyed? Which method was used and what is the associated accuracy?
- Downhole survey orientations – check the drillhole paths in plan and section. Look for anomalies and incorrect orientations. Review the drillhole orientation compared to geology. Is there the potential for a bias due to the orientation?
- Dip direction convention – this will be software specific.
- Magnetic interference – if there is an issue with magnetic interference then what has been done to resolve problem measurements (deleted or corrected)?
- Survey grid system and transformations – what grid is being used and have any transformations been applied to the data?
- End of hole (EOH) depth – are there surveys at the top and bottom of the drillhole? If there is an EOH depth in the collar file does it match the survey depth?

Assay and geology validation

- Table relationships – do all assays have collars, surveys and geology records and do all geology records have collars, surveys and assays?
- Duplicate data – are there duplicate assay or geology records?
- Overlapping intervals or zero length intervals – check for and correct any of these. Some of the mining software packages check for overlaps during the desurveying process.
- Negative values and alphanumeric entries – what are they? All alphanumeric entries should be reset to numeric in your extracted data. Should they be absent or below detection limit? It is recommended that all below detection limit values be reset to half of the detection limit so that they are included as non mineralised values but are still distinguishable from the other results.
- Incorrect values – look at the minimum and maximum values. Check for negatives or errors. Note negative loss on ignition (LOI) values are possible in magnetite iron ore deposits.
- Zero values – it is recommended that zero values not be used in your data. There is always the question of whether they are absent or below detection limit.
- Missing intervals – check why they are missing. Are they missing due to core loss, insufficient sample, still awaiting assay results or is it an error?

- End of hole (EOH) depth – do the assay and geology depths match the survey and collar depths?
- Assay units – what units are the assays in? This is of particular importance if working with data from various sources as some may be in different units.
- Compounds versus elements – which is being assayed for and estimated?
- Total versus recoverable assays – are the grades raw assay results or the recoverable portion of the assay?
- Total assay check – check that the main attributes sum to less than 100%. If working with elements, convert to the compound first if relevant (for example iron to iron oxide).
- Logging – ensure that standard logging codes and procedures have been used. If not then either convert the codes to the standard or flag it as an issue during interpretation. This can be an issue when working with more than one data source (e.g. historical data) where the logging codes have changed. Watch for inconsistencies in logging between programs or geologists. Electronic logging is recommended but if paper logs are in use then ensure that they are legible for data entry purposes. Ensure that all relevant information has been collected.
- Check the correlation between the geophysical and geological logs (i.e. for coal).

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