Mineral resource classification: a comparison of new and existing techniques

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Synopsis

A survey of 120 recent NI 43-101 technical reports was conducted to evaluate the current state of practice regarding resource classification techniques. The most common classification techniques are based on search neighbourhoods (50% of recent reports), drill-hole spacing (30% of recent reports), and/or kriging variance (6% of recent reports). Two new techniques are proposed. The first is based on kriging variance and involves removing one or more drill-holes with the highest weights while performing kriging and using the resultant kriging variance for classification. This technique has the advantages of variance-based techniques and reduces artifacts. The second technique is based on conditional simulation and uses a moving window approach for classification at the desired selective mining unit resolution based on larger production volume criteria. This technique has the advantage of accounting for heteroscedasticity, which is a common characteristic in mineral deposits, and also reduces artifacts since a production volume scale is considered for the actual classification. The drill-hole spacing, search neighborhood, kriging variance, and simulation-based techniques are described and compared for 2D and 3D examples with regular and irregular drilling patterns to highlight the advantages and disadvantages of each method.

Keywords

mineral resource, resource classification, NI 43-101, national instrument, technical reports, kriging variance, simulation, moving window, cross validation,variance.

Introduction

The economic assessment of mining projects includes many factors and resource classification is critical at any stage of mining. The quality of resource classification is a key requirement for accurate economic and environmental risk evaluation. The results of economic assessment are usually reported by companies in order to attract investors. Mineral resource classification standards were created in order to define rules for public disclosure of mineral projects, providing investors with reliable information to assist in making investment decisions. The key idea behind classification standards is to provide a general definition of different categories based on a quantified level of *geological confidence* so that a qualified/competent person can judge the uncertainty based on their past experience with similar deposits.

The estimation of quality/geological confidence depends not only on the quantity of available data, but also on its quality. A number of different quality parameters are discussed by Yeates and Hodson (2006), Postle *et al.* (2000), and Dominy *et al.* (2002). According to the CIM standards on mineral resources and reserves, the classification of mineral resources is dependent on '... nature, quality, quantity and distribution of data...' (Postle *et al.*, 2000). Often companies adopt high standards of quality control in the early stages of projects in order to be able to support Measured resources; therefore, data quality is not considered in this work, all data is assumed to be error-free.

A number of techniques exist for the evaluation of mineable resources based on the quantity and distribution of data. Based on a survey of 120 recent NI 43-101 technical reports, geometric techniques are the most common and typically include drill-hole spacing and search neighbourhood. Techniques based on geostatistics are not as popular, but there are a number of proposals for resource classification, mostly based on ordinary kriging variance.

Typically, the kriging variance is used as a classification criterion by applying thresholds based on the variogram. The application of these thresholds to the kriging variance in order to define the categories was recommended by Royle (1977), Sabourin (1984), and Froidevaux *et al.* (1986) (as cited in Sinclair and Blackwell, 2002). More sophisticated techniques based on kriging variance were proposed by a number of authors. The relative kriging standard deviation, defined as the ratio between kriging standard deviation and the estimated value of a block, can be used (David, 1988). Arik (1999) proposed a classification based on a combination of the ordinary kriging variance and the weighted average of the squared difference between the estimated value of a block and the data values

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used in its estimation. This combined variance is also used in the calculation of a resource classification index proposed later by the same author. The resource classification index includes the estimated value of the block and a calibration factor (Arik, 2002). Yamamoto (2000) proposed a classification technique based on interpolation variance, which is the weighted average of the squared difference between the estimated value of a block and the data values used in its estimation; the weights used are the ordinary kriging weights. Mwasinga (2001) gives a brief description of some other geostatistical classification approaches such as variogram range, kriging variance pdf, confidence limits based on normal and lognormal models, block efficiency, Isobel Clark's classification index, and linear regression slope.

There is also a movement towards the use of conditional simulation techniques in order to support resource classification. Dohm (2005) proposed a methodology that uses conditional simulation to estimate the coefficient of variation (CV) of different production volumes: local (SMU), monthly, and annual. The estimated CVs are later used to define change-of-support factors, which accounts for the correlation between the blocks. These factors are used to define the threshold between classification categories. A block (SMU) with a CV (given by its kriging standard deviation and kriging estimate) small enough to support a monthly production volume with a precision of ±15% with 90% confidence (assuming Gaussian distributions) is classified as Measured. The annual production volume is used to define the Indicated category, and the remaining blocks are assigned to the Inferred category. The main drawback of this methodology is the assumption of normality and generalization of the coefficient of variation since the distribution, whether normal or not, can be assessed after the generation of an enough number of realizations. The use of conditional simulation for classification is also covered by Deutsch *et al.* (2006), Dominy *et al.* (2002), Snowden (2001), and Wawruch and Betzhold (2005).

The output of the survey of recent NI 43-101 technical reports motivated a comparison between the most common techniques, and this comparison motivated the development of new techniques that can take advantage of the recent advances in geostatistics. Although simulation is not used for resource classification in current practice, its possible benefits are investigated. The objective of this paper is to compare the most common techniques and the proposed methods in order to highlight the advantages and disadvantages of each; hopefully, motivating the use of more advanced geostatistical techniques in resource classification.

The proposed kriging variance and cross-validation classification was conceived for the purpose of (1) reducing artifacts that are observed while applying standard kriging variance or regression slope classification, (2) to improve ease of application (fewer subjective parameters) compared to combined or simulation-based techniques, and (3) retain the advantages of variance-based approaches.

The methodology that uses probabilistic citeria applied to the conditional simulation realizations (1) makes use of the advantages of simulation, (2) applies meaningful probabilistic criteria, and (3) increases the resolution of classification based on criteria applied to large scales.

Background

The techniques that are commonly used for classification are presented in the following paragraphs, as well as conditional simulation, which is also covered in this work but is currently not common for resource classification.

Drill-hole spacing

This technique consists of classifying blocks based on the spacing between drill-holes near the block location under consideration. The application of this technique is straightforward when drill-holes are vertical and regularly spaced with minimal deviation. In cases where the drill-holes are irregularly spaced, drilled in different directions, and with significant deviations, the drill-hole spacing may be calculated locally with a search window. Thresholds on drill-hole spacing are often selected based on past experience with similar deposits at the discretion of the qualified person.

Search neighbourhood

This technique consists of classifying blocks based on a distance and constraints related to the number and configuration of the data within the search radius from block to be classified. This technique is most commonly applied by defining estimation passes with different search parameters. Blocks that are estimated by less restrictive passes are classified as Inferred, an intermediate restrictive pass defines the Indicated category, and the most restrictive pass defines the Measured blocks. The most common constraints considered are a minimum number of data, minimum number of drill-holes, and minimum number of informed octants. Again, appropriate thresholds are decided upon based on the experience of the qualified person.

Kriging variance

Kriging is an interpolation technique that minimizes the squared error between the estimated value and the unknown true value. The resultant error variance, also known as the kriging variance, is dependent only on the estimation location, the position of samples, and the variogram. The most common classification approaches, based on the review conducted, require the definition of thresholds to differentiate categories.

The advantage of using kriging variance as the criterion for classification is the consideration of the spatial structure of the variable and the redundancy between samples; however, it often produces classification maps with undesirable artifacts. Artifacts are common near sample location as the kriging variance is very low, resulting in patches of Measured blocks in Indicated zones. Moreover, the kriging variance does not account for the proportional effect which is a common characteristic of earth sciences data and may be important in the high-grade zones where the variance is high.

Conditional simulation

Kriging generates smooth maps that do not consider the proportional effect and the true variance of the data. Conditional simulation corrects for this at the cost of generating multiple realizations that must be processed simultaneously. The mining industry is hesitant to consider conditional simulation as the processing of multiple realizations for mine design is difficult (Dominy *et al.*, 2002); however, it is becoming more common (Snowden, 2001). Each realization generated by simulation is an equally probable representation of the mineral grades and the full set of realizations must be treated as an ensemble, but has the benefit of being able to quantify the uncertainty in the variable under consideration.

The realizations can be scaled to any volume of interest, which is often a selective mining unit (SMU) or a production volume over some time period of interest. The scaled models can be used to evaluate the distribution of grades at a specific support, allowing a meaningful utilization of probabilistic criteria for resource classification. It is up to the qualified person to determine the criteria that would define each category. There are at least three critical parameters to be defined: volume under consideration, precision, and confidence interval (e.g. the values of a quarterly production volume must fall within ±15% of the mean 95% of the time in order to be classified as Measured).

A further advantage of using simulation-based techniques is the possibility of including many other important factors that should be considered for resource classification such the incorporation of all identified sources of error (Dominy *et al.*, 2002). Moreover, a significant proportion of current geostatistical research is focused on generating better conditional simulations; using simulation for classification allows practitioners to take advantage of the numerous advances being made in this field of study.

The use of conditional simulation for resource classification is suggested by many authors such as Wawruch and Betzhold (2005), Dohm (2005), Dominy, *et al.* (2002), and Snowden (2001), which presents it as a better approach to access uncertainty when compared to the kriging variance and other techniques, while Deutsch, *et al.* (2006) recommends its use only as a supporting tool while the final classification criteria should remain geometric. The reason for this is because the results of classification are highly dependent on the modeller assumptions and the parameters chosen, making resource disclosure less transparent to investors.

Methodology

Even with geometric-based classification there are a number of subjective parameters, i.e. drill-hole spacing classification can be automatically calculated by a computer algorithm or handle-defined bench-by-bench. A description of two popular techniques is provided – drill-hole spacing and search neighbourhood; a description of two proposed techniques follows based on cross-validation variance and conditional simulation.

Drill-hole spacing

As mentioned, the calculation of drill-hole spacing is not straightforward for irregular drilling patterns. Here, the calculation of drill-hole spacing is based on Equation [1], which is calculated with a circular search and corrected to represent a squared spacing i.e. 50 m × 50 m (DHS = 50 m).

$$DHS(u) = R(u)\left(\frac{2}{n}\right)^{\frac{1}{2}} \quad [1]$$

where u is the location of the block to be classified, $DHS(u)$ is the calculated drill-hole spacing at location u, n is the user-defined parameter of the n-closest drill-holes that intersect the horizontal plane, and $R(u)$ is the average distance between the centre of the block and the nth and $(n+1)$th drill-holes. In order to reduce artifacts and generate smoother classification maps, a new technique is proposed where multiple values of n are considered and the resulting $DHS(u)$ is averaged (ADHS) to provide more spatially consistent results in the case of irregular drill-hole spacings.

Search neighbourhood

Two parameters are required to define a search neighbourhood: the search radius and the minimum number of drill-holes. The classification performed in this way is similar to classification based on DHS using a single threshold value equal to the equivalent drill-hole spacing (EDHS), which can be calculated using an equation similar to the equation used for DHS considering the search radius (R) and the minimum number of drill-holes (n_{dh}) used as parameters for search neighborhood classification (Equation [2]).

$$EDHS(u) = R\left(\frac{2}{n_{dh}}\right)^{\frac{1}{2}} \quad [2]$$

Kriging variance

In this work, the thresholds that define different categories are selected according to a desired drilling spacing. The kriging variance of a block located at the centre of a regular grid that would support Measured resources becomes the threshold between Measured and Indicated, and the value of the kriging variance of a block in the centre of a regular grid that would support Indicated resources becomes the threshold between Indicated and Inferred resources.

Cross-validation variance

A new classification technique is proposed in order to retain the advantages of the kriging variance over the geometric techniques and to reduce artifacts. The cross-validation variance (CVV) is calculated by removing one or more drill-holes with the highest weights while performing block kriging and using the resultant kriging variance to classify the blocks. This technique is suitable for regular and irregular drilling patterns; accounts for spatial structure and redundancy between data; and reduces artifacts caused by using the kriging variance alone. Classification is done by (1) removing the drill-hole with highest kriging weight, (2) calculating kriging variance using the surrounding data, and (3) applying a threshold for classification.

The number of drill-holes to be removed and thresholds are defined by the user in order to minimize the undesirable 'holes' and 'patches' that are created with conventional kriging variance classification. An improved reduction of artifacts can be achieved by using the average CVV resulting from removing different numbers of drill-holes.

Moving window classification based on conditional simulation realizations

It is desirable to have a classification model at SMU scale

(Wawruch and Betzhold, 2005), but one of the difficulties of using probabilistic criteria (i.e. the values must fall within ±15% of the mean 95% of the time) for resources classification is that in order to classify at the SMU scale, the probabilistic criteria have to be less restrictive in order to allow for measured resources. Moreover, artifacts are often generated close to drilling locations where blocks are classified as Measured even in sparsely sampled areas. These artifacts are undesirable (Deutsch *et al.*, 2006). This is often remedied by classifying resources based on larger volumes which may represent monthly, quarterly, or yearly production. In this case the probabilistic criteria can be more restrictive, leading to more control at a meaningful scale with fewer artifacts.

The quarterly production volume is much larger than the SMU size and its shape, volume, and position are often unknown as these depend on a detailed mine plan that is certain to change as more data is collected. However, the shapes of these larger panels can be determined from prior experience with similar deposits in conjunction with relevant information such as a grade variability model (Wawruch and Betzhold, 2005). Different origins for this large-scale block model lead to different classification models, and because of its size the classification is made at low resolution (Figure 1).

In order to obtain the desired SMU-scale classification resolution while minimizing artifacts, a large production volume is required but the panel positioning is not deterministic at the stage of classification. A local classification is proposed that considers a window representing the production panel centred at each SMU block which is classified according to the classification of that panel (Figure 2).

The specific values for the probabilistic criteria to be used is out of the scope of this work; it is certainly case-specific and requires expert judgment, as with all classification approaches. The parameters usually range between ±10% to ±30% for precision and between 95% and 80% for confidence intervals (Dohm, 2005; Dominy *et al.*, 2002; Wawruch and Betzhold, 2005; Yeates and Hodson, 2006). The criteria used in this work are within these ranges.

Survey of NI 43-101 reports

The public disclosure of mineral project results by companies listed on Canadian exchanges must follow the Canadian Institute of Mining (CIM) standards for mineral resources. The documents that contain this disclosure are known as NI 43-101 and are publicly available through the SEDAR website (SEDAR, 2013). A survey of NI 43-101 technical reports issued in 2012 was conducted to evaluate the current state of practice regarding techniques used in reserve classification. The collected information relevant to this work are the classification technique employed, the chosen criteria, and the drilling pattern. From a total sample of 281 reports, only 120 had sufficient information to determine the technique used for classification. The remaining 161 reports are: those without resource classification; reports with only Inferred resources; reports with classified resources but without clear explanation of the methodology applied; and, reports on the same deposit that were already included in database.

The most common classification techniques are (Table I): search neighbourhood (SN); drill-hole spacing (DHS); kriging variance (KV); a combination of drill-hole spacing and search

Table I

Analysis of classification methods used in NI 43-101 technical reports published in Canada in 2012 (120 reports were considered)

Type	% of reports	Regular drilling (%)	Irregular drilling (%)
SN	50	3	97
DHS	30	75	25
SN + DHS	3	42	58
SN + KV	3	0	100
KV	3	0	100
Other	10	8	92

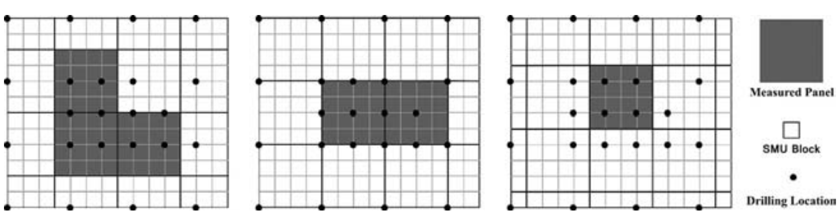

Figure 1—Different classification results for different origins based on a larger production volume scale

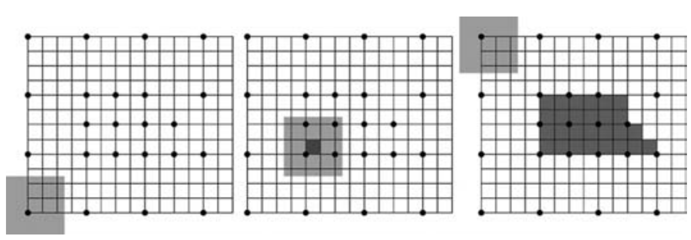

Figure 2—Moving window classification. Left: the SMU block is not considered Measured as the uncertainty in the larger production volume (light grey) is large. Centre: the SMU block is considered Measured as there is low uncertainty in the larger production volume (light grey) due to the denser data. Right: SMU blocks considered Measured

neighbourhoods (DHS+SN); and a combination of search neighbourhood and kriging variance (SN+KV). In general the DHS technique was preferred when drilling was regular; as this is often the case in mining operations. Often the SN technique is used when drilling was irregular as defining a consistent DHS to apply to the deposit is difficult. Kriging variance is used to account for geological continuity when the variogram is considered well defined, but manual treatment of the results was required to remove artifacts in most cases.

Comparison between techniques

The drill-hole spacing, search neighbourhood, kriging variance, simulation, and cross-validation variance are described and compared for 2D and 3D examples with regular and irregular drilling patterns to highlight the advantages and disadvantages of each. The 2D model was generated by an unconditional sequential Gaussian simulation (SGS) and sampled with a regular and irregular grid (Figure 3). The 3D example uses data from drill-holes on a porphyry copper-gold deposit (Figure 4).

Classification for the 2D regular grid is trivial, but is included as a benchmark for the techniques. It was created to resemble a constant thickness (10 m) tabular deposit in which the modelling block size is 25 m by 25 m and the quarterly production is given by a block size of 150 m by 150 m. For the regular 2D example the model is sampled by three regular grids: 200×200 m; 100×100 m; and, 50×50 m. For the irregular 2D example a random component was added to the coordinates of the regular grid before sampling. The variogram of the data is a nested structure of two isotropic spherical models with ranges of 200 and 300 m with 25% and 75% of contribution to the sill respectively.

For the 3D example the variogram of the data is a nested structure with three spherical models and a nugget effect of 15% (Equation [3]).

$$\lambda(h) = 0.15 + 0.18 \times Sph_{\substack{av=15m \\ ah=23m}} + 0.17 \times Sph_{\substack{av=180m \\ ah=23m}} + 0.50 \times Sph_{\substack{av=180m \\ ah=100m}} \qquad [3]$$

The 3D example has two nominal drill-hole spacings of 50×50 m and 25×25 m. The modelling block size for the 3D example is 15 m by 15 m by 10 m and the quarterly production is given by a block size of 150 m by 150 m by 60 m.

Results and discussion

2D regular

The synthetic 2D example with a regular drilling pattern is considered first to visualize the results of each technique (Figure 5). For DHS the Measured blocks are those within the area drilled at 50×50m grid with extrapolation of half a spacing (25 m), Indicated blocks are those within the area drilled at 100×100m with extrapolation of 50 m, and Inferred blocks are those within the area drilled at 200×200 m.

For the SN classification the parameters were chosen by a visual sensitivity analysis in order capture the areas considered Measured, Indicated, and Inferred. Blocks with at least 8 drill-holes within 100 m are considered Measured (EDHS = 50 m), Indicated blocks are those with at least 8 drill holes within 200 m (EDHS = 100 m).

For the KV classification the thresholds were defined based on same drill-hole spacing used for DHS classification. The threshold between Measured and Indicated is 13% of the sill and the threshold between Indicated and Inferred is 31% of the sill.

The number of drill-holes removed for the CVV method is one and the thresholds were chosen by a visual sensitivity analysis in order to reduce artifacts. The removal of drill-holes increases the kriging variance for each block, which leads to higher thresholds when compared to using the KV

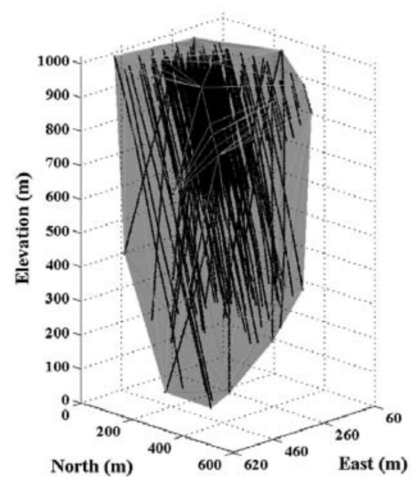

Figure 4—3D samples used to compare techniques

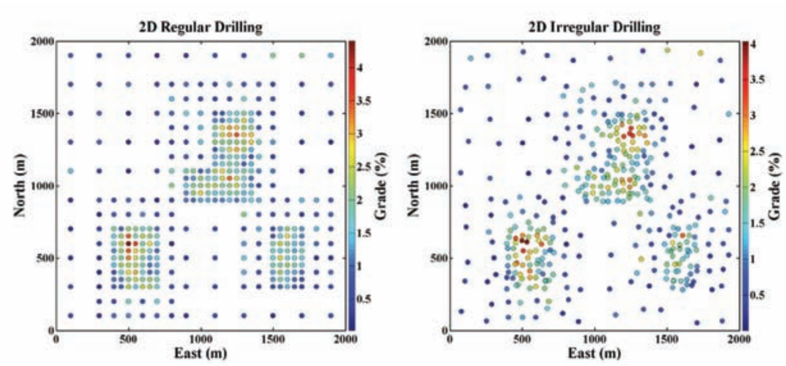

Figure 3—2D models used to compare techniques. Left: regular sampling. Right: Irregular sampling

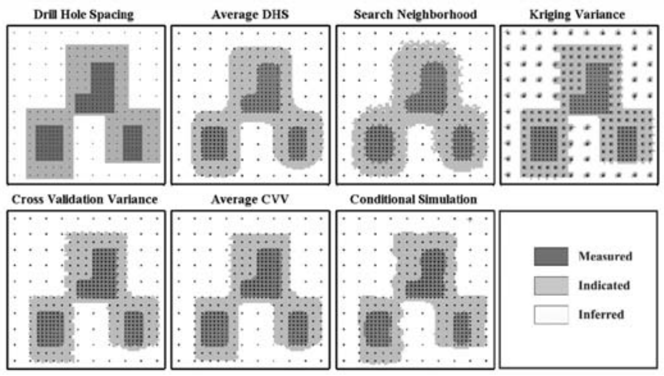

Figure 5—Classification results for the 2D regular grid. Axes dimensions: 2000 m by 2000 m. The upper left classification is the assumed correct classification for this simple synthetic example

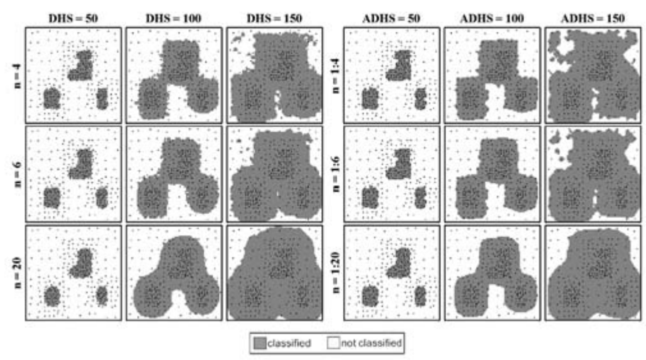

Figure 6—Sensitivity on DHS parameters. (Left: single parameter; right: average DHS searching 1 to 4, 1 to 6, and 1 to 20 drill-holes). Axes dimensions: 2000 m by 2000 m

technique. The thresholds used were 21% and 45% of the sill. For the average CVV classification, the number of drill-holes removed was one and two and the thresholds were 24% of the sill and 50% of the sill, again selected based on visual inspection.

The classification based on conditional simulation was performed with the proposed technique. In order to define Measured blocks the quarterly production panel must have a precision of at least ±15% with 95% of confidence, while Indicated must have a precision of ±30% at 80% confidence interval.

It will be noticed that for this synthetic example, the DHS zones defined by hand (titled Drill Hole Spacing in Figure 5) were matched well by the majority of the techniques as this is a fairly easy set of drill-holes to classify. As expected, the KV performed well in classifying different zones but with the problem of artifacts (patches) close to drilling locations that are successfully removed using the proposed CVV methodology. Artifacts were also successfully avoided using the proposed methodology for conditional simulation. In this case there is no anisotropy and the proportional effect is not expressed.

2D irregular

The 2D example with irregular drilling is used to visualize the effect of parameters for each technique and to visualize the adequateness of each technique in situations in which classification is not straightforward.

Drill-hole spacing

A visual analysis of the parameters for DHS is shown in Figure 6. Increasing the number of data used in calculation reduces the artifacts but also increases misclassified blocks compared with the assumed correct manual classification (Figure 5 – upper left). There is no control on the search radius considered as it is a function of the block location and number of data searched (n). Data far from a block may inadvertently assign a higher category for a block; a small number of drill-holes is recommended to avoid this problem. The use of average DHS (Figure 6 – right) removes the reliance on selecting a single value of n. More accurate (closer to the known 'by hand' technique) and smoother (fewer holes and patches) maps can be achieved using the average.

Search neighbourhood

A visual analysis of the parameters for the SN technique is shown in Figure 7. Classification based on SN requires two parameters (search radius and minimum number of drill-holes) and performs similarly to DHS for irregular drilling patterns. The classification maps may require post-processing to reduce noise on the classification borders.

Kriging variance/cross-validation variance

A visual analysis of parameters for the CVV technique is shown in Figure 8. Blocks that are close to redundant drill-holes tend to stay in the same category as with the conven-

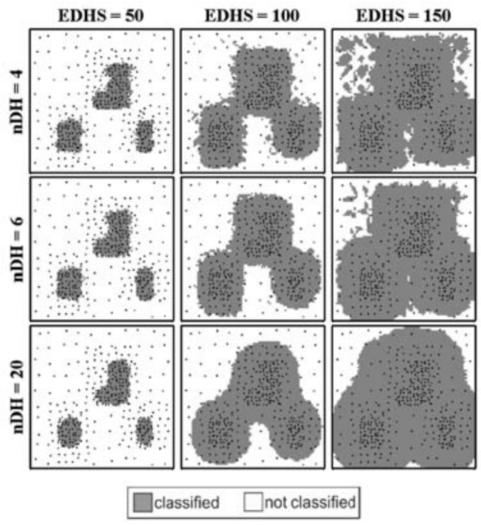

Figure 7—Sensitivity on SN parameters. Axes dimensions: 2000 m by 2000 m

tional KV method; blocks that are located close to isolated drill-holes tend to be downgraded. This is a desirable characteristic but a balance must be achieved between removing 'patches' and creating new 'holes'. In general, the technique reduces the artifacts compared to using the KV alone (Figures 5, 11, and 12). If the removal of one drill-hole is not sufficient for removing artifacts the average CVV may be considered.

Conditional simulation

A visual analysis of parameters for classification based on conditional simulation using the proposed methodology is shown in Figure 9. The conventional classification for small (SMU) and large scale (panel) is compared with the proposed methodology for classifying at a local scale resolution by using large-scale criteria (Figure 10). The chosen criteria for SMU scale classification were precision of ±30% with 90% confidence for Measured and ±30% with 50% confidence for Indicated. For the large scale the criteria were precision of ±15% with 95% confidence for Measured and ±30% with 80% confidence for Indicated.

The proposed technique of centring a production volume on each SMU (Figure 10 right) reduces artifacts and does not have the undesirable reliance on a fixed large-scale grid, where panels clearly contain part Measured and part Inferred SMU blocks (Figure 10 centre).

Classification results

The result of classification for the 2D irregular case is shown in Figure 11 for all techniques and illustrates how different techniques considered perform in a non-straightforward way.

The DHS was calculated using Equation [1]. Blocks with DHS less than or equal to 50 m are Measured, blocks with DHS less than or equal to 100 are Indicated, and the remaining blocks are Inferred.

For SN classification the parameters were chosen by a visual sensitivity analysis in order to take the best combination that captured the areas considered Measured, Indicated, and Inferred. Blocks with at least 8 drill-holes within 100 m are considered Measured (EDHS = 50 m), Indicated blocks are those with at least 8 drill-holes within 200 m (EDHS = 100 m).

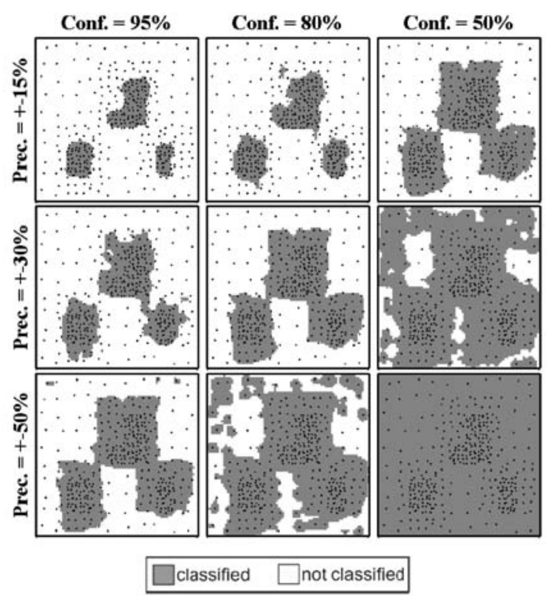

Figure 9—Sensitivity on conditional simulation parameters. Axes dimensions: 2000 m by 2000 m

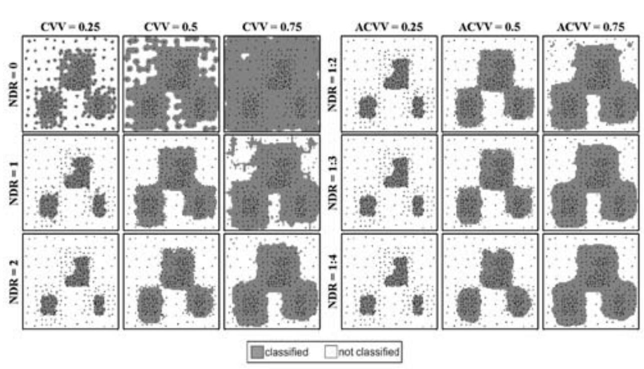

Figure 8—Sensitivity on cross-validation variance (left: single parameter; right: average CVV removing 1 to 3, 1 to 4, and 1 to 5 drill-holes). Axes dimensions: 2000 m by 2000 m. Removing 0 drill holes, NDR=0, is equivalent to the traditional KV technique. The thresholds 0.25, 0.5, and 0.75 are proportions of the sill

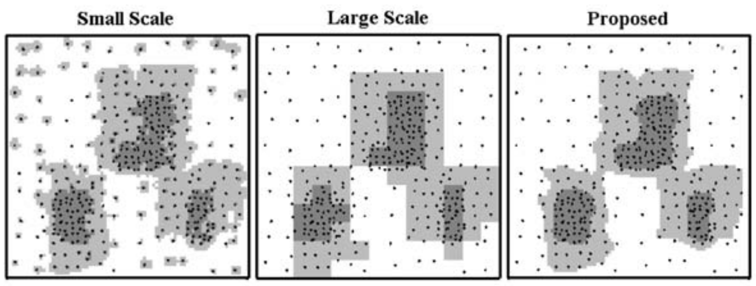

Figure 10—The classification based on conditional simulation for small scale, large scale, and the proposed methodology. Axes dimensions: 2000 m by 2000 m

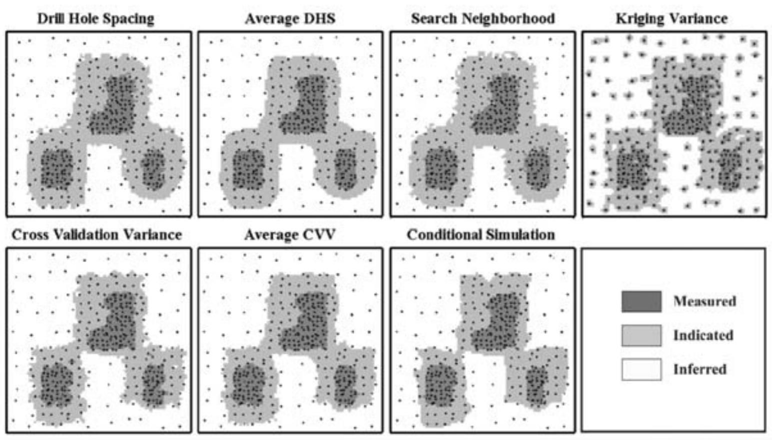

Figure 11—Classification results. Axes dimensions: 2000 m by 2000 m

For the KV classification the thresholds were defined based on a regular grid of 50 × 50 m for Measured and 100 × 100 m for Indicated. The threshold between Measured and Indicated is 13% of the sill and the threshold between Indicated and Inferred is 31% of the sill based on an equivalent DHS.

The number of drill-holes removed for CVV method is one and the thresholds were chosen by a visual sensitivity analysis in order to minimize artifacts. The thresholds used were 20% and 45% of sill. For the average CVV method the number of drill-holes removed was one and two and the thresholds were 23% and 52% of the sill.

The classification based on conditional simulation was performed with the proposed technique. In order to define Measured blocks the quarterly production panel must have a precision of at least ±15% with 95% confidence, while Indicated must have a precision of ±30% at 80% confidence interval.

3D example

The 2D examples are appropriate for vertically drilled holes, but mineral classification problems are often three-dimensional with a significant proportion being irregularly drilled as a high degree of geological confidence requires drill-holes intersecting the orebody in different directions (Yeates and Hodson, 2006). For the 3D example, a sensitive analysis similar to that made for the 2D irregular case was performed in order to select the parameters for various classifiers with exception of the classification based on conditional simulation. The probabilistic criteria used were a precision of ±15% with 95% confidence for Measured and ±30% with same confidence interval for Indicated. The classification models are shown in Figure 12.

For this example the grade values were estimated by ordinary kriging and the resources were calculated and classified with each technique. The results of resource calculation and classification are given in Figure 12 and Figure 13.

The quantitative results for geometric methods and proposed techniques were similar, with a slight increase in the Indicated category for the proposed techniques (CVV and SIM). Using the KV, there was a considerable increase in the Measured category due mainly to the 'patches' artifacts that are common with this classification technique. Ignoring the KV technique, it is interesting to note that the Measured and Indicated results are surprisingly consistent across all techniques. Of course, the benefit of incorporating simulation into classification is that local classification can be more accurate as data redundancy and anisotropy can be incorporated.

Conclusions

From a review of the most recent Canadian 43-101 reports, the most common techniques used for resource classification are geometric in nature. These techniques do not account for the spatial continuity of the variables nor redundancy between data, but typically result in classification maps that have less artifacts and are less sensitive to modelling parameters (i.e. kriging and simulation parameters).

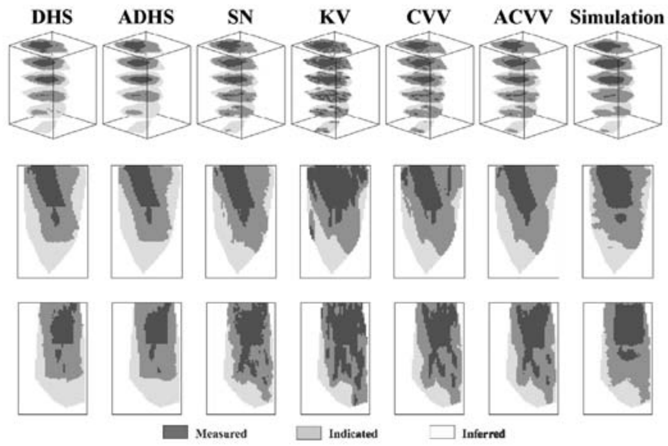

Figure 12—3D example - classification results. Axes sizes: 1000 m (vertical); 600 m (east); and 560 m (north)

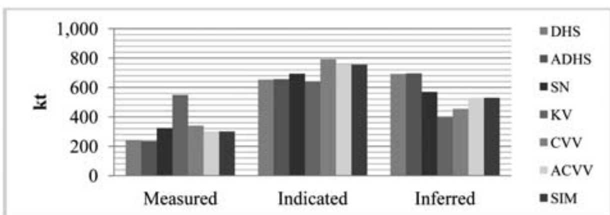

Figure 13—Resource classification results, showing the metal tonnage. The total tonnage results were very similar

The advantage of using variance-based techniques as opposed to geometric is the opportunity to account for grade continuity and data redundancy, which can significantly affect the local uncertainly that classification should be measuring. The kriging variance captures this information but often results in artifacts when used in classification. The combination of cross-validation with the kriging variance is able to reduce these undesirable features and incorporate known information on spatial continuity. Although the kriging variance incorporates these desired features, it does not account for the proportional effect, which is a significant limitation for the highly skewed distributions common in the mineral industry. Simulation-based classification has the potential to overcome this limitation. The proposed methodology is capable of performing classification at a typical block modelling scale (often SMU) but with reduced artifacts as a production volume scale is considered for the final classification. The main limitation of conditional simulation for classification is the sensitivity to key parameters such as the covariance function and trend model, which are very dependent on modelling assumptions, making resource disclosure less transparent to investors.

Many methodologies for classification have been proposed in recent years, but only a few of them are actually used in practice. The techniques proposed in this paper represent viable alternatives for resource classification. As with all resource classification techniques, it is the responsibility of the practitioner to assess the appropriateness of the final result based on knowledge of the deposit.

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