Local Self-Healing: a Method to Incorporate Geological Interpretations Into Sequential Indicator Simulation

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Abstract

In many mines it is the geological (lithological) uncertainty rather than the grade uncertainty that has the greater economic significance. In the absence of precise knowledge of the deposit geology, geological models of these types of deposits that are used to constrain spatially the estimated (or simulated) grade values may influence significantly the contained metal. Methods for assessing geological uncertainty quantitatively are rarely considered due their perceived inability to consider exhaustive geological interpretations, and resulting models often appear geologically unrealistic. Multiple-point statistical approaches that produce realistic geological models call for geological training images (analogues such as geological interpretations). However, these training images are used to condition (influence) locally the resulting geological models based on global geological characteristics rather than interpreted local geological features.

It is proposed to integrate a simple algorithm into the well-known sequential indicator simulation (SIS) algorithm to correct locally the simulated realisations for geological interpretations. The algorithm is called local self-healing because the correction is administered with the aid of a priori local distributions, and the size of the correction depends on the magnitude of the problem (local confidence in the interpretation). This new approach to stochastic simulation of lithology and its impact on contained metal is demonstrated for a lode-style gold deposit.

Introduction

Stochastic simulation of lithology (or geology) may be desirable to account quantitatively for lithological controls on mineralisation. For example, the spatial distribution of gold grades is often controlled by quartz vein sets in lode-style deposits. Simulated models of such deposits must incorporate all sources of uncertainty rather than simply the uncertainty modelled by the variogram of sampled gold values. In many cases it is the lithological uncertainty that has the greater economic significance. For example, in lode-style gold deposits quantifying accurately the financial uncertainty relies on the ability to locate and define spatially the individual lodes. In the absence of precise knowledge of the lode geometry the space of uncertainty in the simulated gold values may be significantly over/underestimated if a single deterministic geological interpretation is used to constrain spatially the simulated gold values.

Consider the drill-hole data and the geological interpretation shown in Figures 1 and 2 respectively. Stochastic images conditional to the drill-hole data (Figure 3) generated by sequential indicator simulation (SIS) cannot account for the geological interpretation. This can be observed by comparing each SIS realisation in Figure 3 to the left-hand plot in Figure 2. Note that, all stochastic images in this paper have been cleaned using a maximum a posteriori algorithm (Deutsch, 1998). As the geological interpretation is exhaustive an indicator cokriging system (ScIS) would be unstable. Furthermore, ScIS is unable to account for the uncertainty (or confidence) in the geological interpretation, shown in the right-hand plot in Figure 2. A colocated cokriging framework would ignore the geological interpretation at simulated locations other than the drill sample locations. Plurigaussian simulation can account for complex geological relationships stochastically (Skvortsova et al., 2000), but not exhaustive secondary information. This drawback is also a feature of most heuristic algorithms (e.g. simulated annealing, local search) and object-based algorithms (e.g. boolean, marked-point models). Srivastava (2005) discussed a complex indicator probability field simulation approach that considered locally varying anisotropy and families of variogram functions to generate plausible two-phase realisations.

Multiple-point statistical approaches to sequential simulation (eg Arpat and Caers, 2004) that produce realistic geological models call for geological training images (analogues such as geological interpretations). However, these training images are used to condition (influence) locally the resulting geological models based on global geological characteristics rather than interpreted local geological features.

Consequently, local geological interpretations in which great confidence is placed may not be honoured. Some simple method of incorporating the geological interpretation and its local confidence in stochastic simulation would represent an improvement over current techniques for simulating categorical variables.

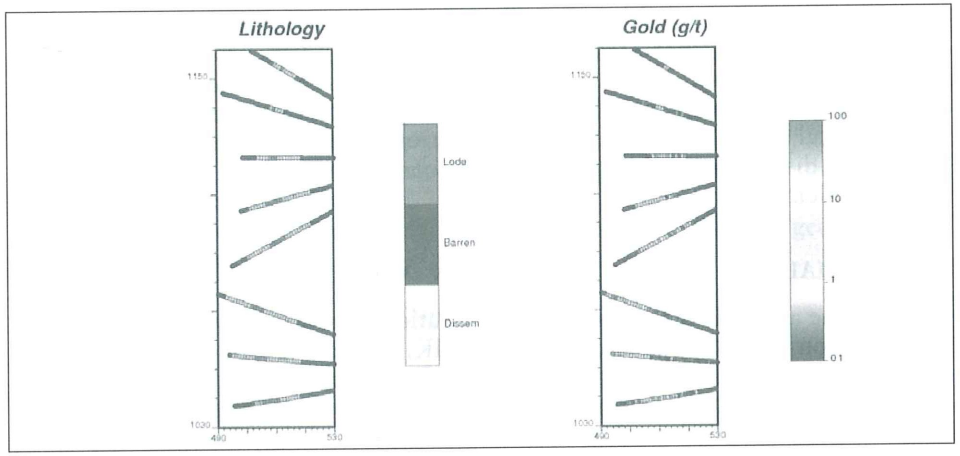

Figure 1: Drill hole data: (left) lithology; and (right) gold assays (ppm).

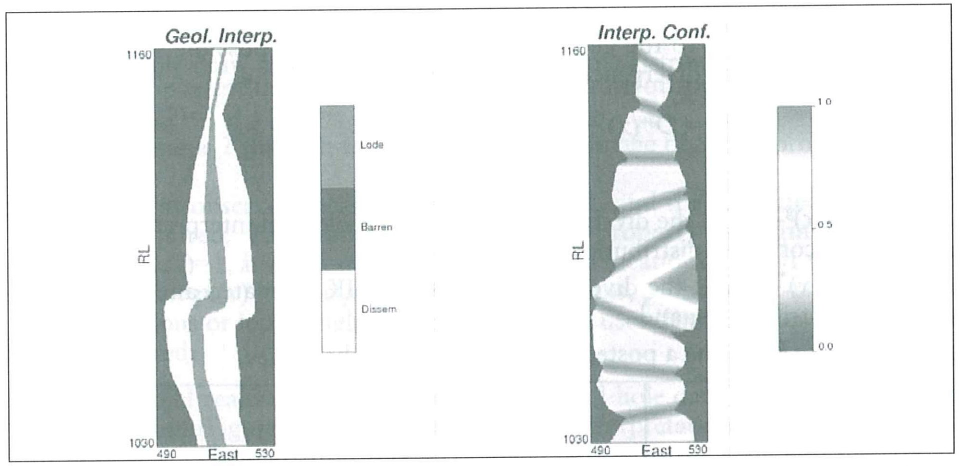

Figure 2: Geological interpretation (left) and confidence (right) (Note: higher values indicate lower confidence).

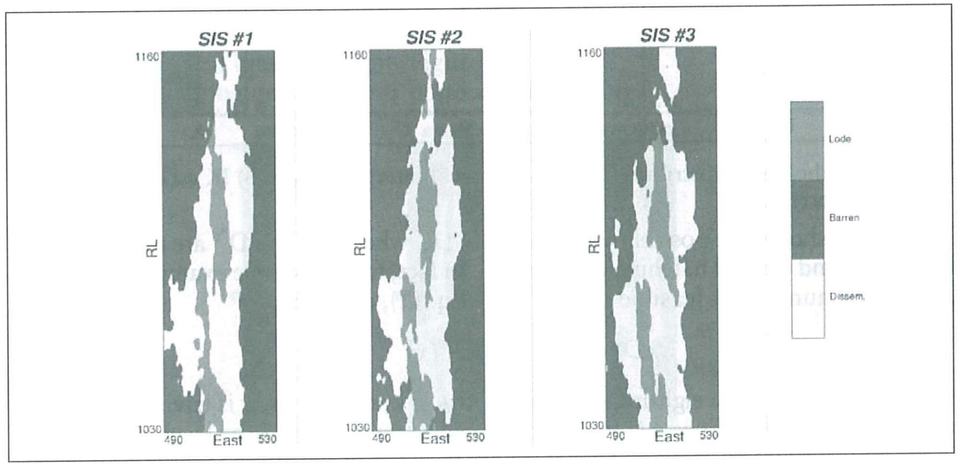

Figure 3: SIS realisations.

The specific problem that is addressed in this paper is the stochastic simulation of categorical variables that are geologically realistic and accurately represent the geological uncertainty. It is proposed to integrate a simple algorithm into SIS to correct locally the simulated realisations for geological interpretations. The algorithm is called local self-healing because the correction is administered with the aid of a priori local distributions, and the size of the correction depends on the magnitude of the problem.

Sequential Indicator Simulation With Local Self-Healing

Consider the a priori local distribution at location x associated with the geological interpretation ($p_k(x)^g$) and indicator kriging (IK) estimate ($p_k(x)^*$), shown in Figure 4 for three lithologies, A, B, and C. Note that, in this paper the a priori local distribution at location x is considered only to be the local (point) interpretation, however, it could easily be expanded to consider the local neighbourhood. The idea of local self-healing is to modify the indicator kriging (IK) distribution to account for the geological interpretation. Straightforward Bayesian updating and minimising the cross-entropy (Kullback, 1959) would invariably provide an a posteriori distribution identical to the geological interpretation. A possible solution is to minimise the directed divergence between $p_k(x)^g$ and $p_k(x)^*$, *i.e.*

minimise $$D(x) = D^{gc}(x) + D^{*c}(x) \quad (1)$$

where

$D^{gc}(x) = |p_k(x)^g - p_k(x)^c|$, the divergence between the geological interpretation and an a posteriori corrected distribution;

$D^{*c}(x) = |p_k(x)^* - p_k(x)^c|$, the divergence between the IK estimated and a posteriori corrected distributions; and

$p_k(x)^c$, $k=1,\ldots,K$ are the a posteriori or corrected probabilities.

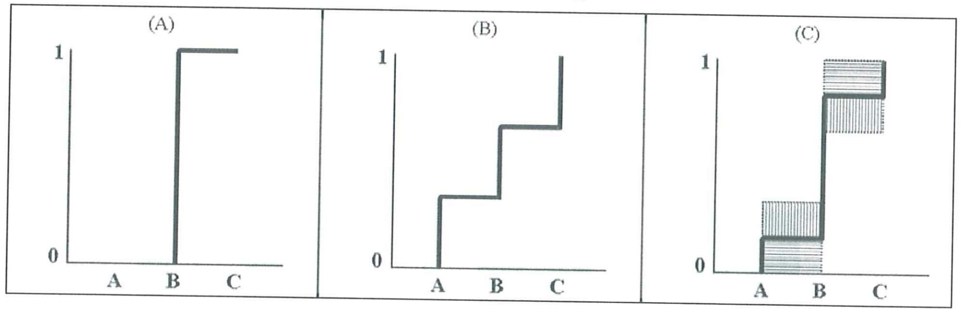

Figure 4: Lithological distributions: (A) geological interpretation; (B) IK estimate; and (C) corrected.

Figure 4(C) shows one possible solution to Eq. (1), where D^{gc} and D^{*c} are represented by horizontal and vertical hatching respectively. In fact, for this simple example there exists an infinite number of feasible solutions to Eq. (1), given by,

$$\lambda D^{gc}(x) = (1-\lambda) D^{*c}(x) \quad (2)$$

where λ (0 λ 1) is a weighting parameter. If λ is known, then it is trivial to calculate the corrected probabilities $p_k(x)^c$. It is proposed to interpret λ as the level of confidence in the geological interpretation. Then, SIS with local self-healing (SISLSH) for K lithologies proceeds as follows:

1. Transform the observed datum $s(x_\alpha)$ into K indicator datasets $\{i(x_\alpha;k), =1,\ldots,n; k=1,\ldots,K\}$ using a binary transform $i(x_\alpha;k)=1$ if $s(x)=k$, and zero otherwise
2. Randomly select a location x_β at which no s-value exists.
3. Determine the K conditional probabilities Prob $\{(S(x_\beta)=k|(n)\}=p_k(x_\beta)^*$, $k=1,\ldots,K$ using IK and n indicator transforms of the original data $i(x_\alpha;k)$ or previously simulated locations $i^l(x_\beta;k)$
4. Correct the local probabilities from step (3) to account for the geological interpretation, *i.e.*:
5. $$p_k(x_\beta)^c = (1-\lambda(x_\beta))p_k(x)^* + \lambda(x_\beta)p_k(x)^g,\ k=1,\ldots,K \quad (3)$$
   where $p_k(x)^g=1$ is the geological interpretation and $\lambda(x_\beta)$ $(0 \leq \lambda(x_\beta) \leq 1)$ is the geological confidence.
6. Build a cumulative distribution function of s at x_β with probability interval [0,1] and K intervals:
   $$[0,\ p_1(x_\beta)^c,\ p_1(x_\beta)^c + p_2(x_\beta)^c, \ldots, \sum_{k=1}^{K-1} p_k(x_\beta)^c,\ 1] \quad (4)$$
7. Randomly draw a simulated value $s^l(x_\beta)$ from the distribution generated in step 5
8. Add the simulated value to the K conditioning indicator datasets, *i.e.* $i^l(x_\beta;k)=1$ if $s^l(x_\beta)=k$, and zero otherwise, $k=1,\ldots,K$
9. Repeat steps 2 through to 7 until a complete image of $S(x)$ is produced.

Obviously at observed locations ($x_\alpha=x_\beta$) $\lambda(x_\beta)=1$, and the estimated probabilities are not required. Alternatively, the exactitude property of kriging ensures that $p_k(x_\beta)^*=i(x_\alpha;k)=1$, $k=s(x_\alpha)$, $\alpha=\beta$. At non-observed locations $\lambda(x_\beta)<1$ and there is no restriction for $p_k(x)^g=1$ and $p_{k'}(x)^g=0$ for $k' \neq k$. Thus, probabilistic-based geological interpretations or local neighbourhoods based on user-defined templates could also be considered.

Three SISLSH realisations conditional to the drill-hole data (Figure 1), geological interpretation (Figure 2), and confidence in the interpretation (Figure 2) are shown in Figure 5. These realisations were generated with the same parameters and simulation path as the SIS realisations shown in Figure 3, hence provide a direct comparison between SIS and SISLSH. Note that:

- The SISLSH images in Figure 5 appear geologically realistic, when compared to the geological interpretation (Figure 2).
- Locally varying anisotropy is honoured implicitly.

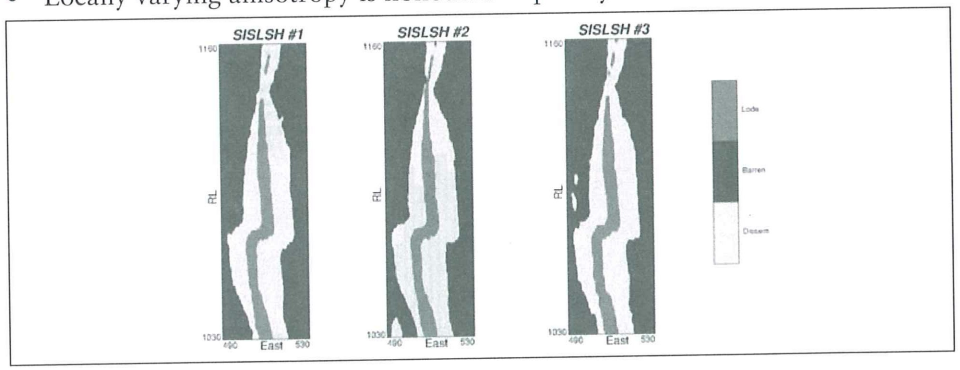

Figure 5: SISLSH realisations.

Case Study

Figure 1 represents underground drill-hole data from a lode-style gold deposit that has been modified to maintain confidentiality. The lode in the central part of the plot is known to be a folded quartz vein, as shown in Figure 2. The rest of the geological interpretation simply joins the drill hole intercepts with essentially straight lines. However, at the higher levels, mining has shown that the lode commonly pinches out. The disseminated material represents quartz stringer veins in altered host rock that contain low grade gold mineralisation that is rarely economic.

To evaluate the impact of lithology on the contained metal, 500 realisations of gold values were generated with sequential Gaussian simulation (SGS). Two scenarios were considered:

1. the geological interpretation (Figure 2) was used as a deterministic wireframe to constrain all 500 SGS realisations; and
2. the geological interpretation and confidence (Figure 2) were used to generate 500 SISLSH models of lithology. Then, each SGS realisations was constrained to an alternate SISLSH model.

Figure 6 shows the distribution of metal content within one lode for both scenarios. Note that, the expected metal content is the same at 225,000 ounces (oz) of gold. However, the uncertainty in metal content is significantly higher when the uncertainty in lode geometry is considered. Figure 6 shows that when uncertainty in gold grades is the sole risk criteria considered, the lode may contain 166,000 to 293,000 oz. When both gold grades and lode geometry are used to consider risk, the lode may contain 152,000 to 330,000 oz. Thus, by considering lode geometry there is greater downside risk and upside potential.

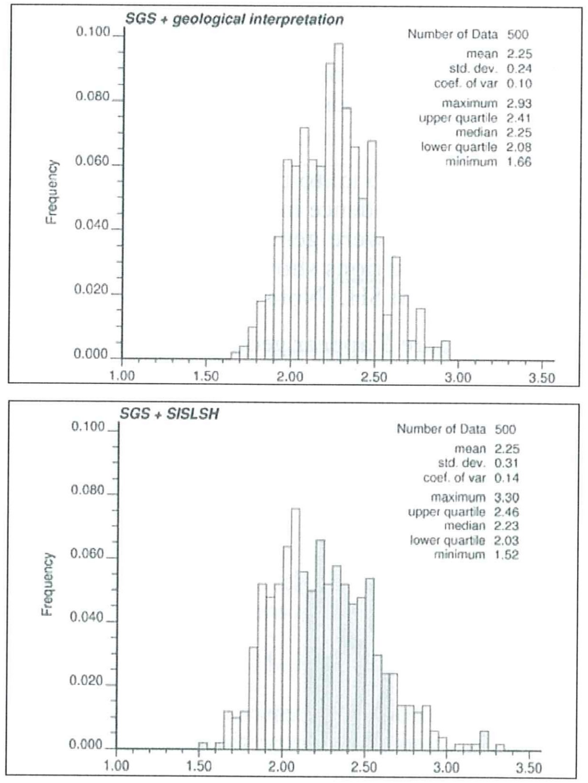

Figure 6: Histograms of metal content (oz x 10^5).

Conclusions

This paper presented a simple methodology for probabilistic modelling the geological architecture of a mineral deposit using a modified sequential indicator simulation algorithm. It is useful in relatively sparsely drilled deposits where the geological correlations between drill holes can be established with reasonable certainty, but the precise location of economically significant geological domain boundaries is uncertain. The methodology accounts implicitly for interpreted locally varying anisotropy.

A probabilistic treatment of geological domains will improve the evaluation of mineral deposit uncertainty and risk assessment. The case study presented in this paper demonstrated that by considering lode geometry uncertainty, significantly greater downside risk and upside potential was present in the gold deposit that previously recognised by simply considering gold grade uncertainty within a deterministic wireframe. A recent study by Srivastava (2005) contained similar observations. The consideration of geological uncertainty in mineral deposit risk assessment should be a primary focus, and not ignored as the present common practice.

References

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