



Approaches to characterize the uncertainties related to stochastic simulations

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Kriging vs. Simulation

Kriging

- Generalized least-squares regression algorithms
- Kriging variance is not a measure of uncertainty
- An artificially smoothed representation of reality
- Smoothing is undesirable when the aim is to outline areas characterized by high or low values

Simulation

- Reproducing characteristics of the sample distribution
- For preserving spatial variation of the studied attribute
- Modeling local short scale variability
- Generating equally probable realizations that allow characterizing uncertainty of the modeling process



Sequential Gaussian Simulation vs. Sequential Indicator Simulation

SGS

SIS

- Fast and straightforward
- Assumes a parametric distribution
- Maximizes the scattering of extreme values in space
- Does not allow significant spatial correlation of extreme values

- Reproducing characteristics which are not multigaussian
- Accounting for class-specific patterns of spatial continuity
- For cases when extreme values could be better correlated in space than medium values



The studied geometries

Slice 1

Slice 2





floodplain sediments

channel mouth bar



Slice1 - Representativity





Statistics of Slice1 outputs

Minimal differences between pooled outputs at different resolutions
SGS considerably better at reproducing the model distribution

SGS Pooled



SGS Median





SIS Pooled



SIS Median





Slice1 SGS QQ plots for pooled realizations and MD estimations

- Better fit of pooled data in the direction of smaller resolutions, but MD type estimates tend to wash this effect away
- Less grid nodes better reproduction of model distribution





Slice1 SIS QQ plots for pooled realizations and MD estimations

- Reproduction of statistics for pooled realizations improve toward lower grid resolutions, but MD type estimates still hardly follow this
- An overall less accurate fit than in the case of SGS





Slice1 MD type visualizations

- Both far from reality, but true to what one might expect from the simulation algorithm itself
- SGS maximizes the scattering of extreme values while SIS is more pattern oriented



Original image

SIS



Uncertainty of the SGS estimations

- Higher entropies dominate over the area
- CV confirm the entropies everywhere entropy is a stricter measure of uncertainty than CV
- Entropy and CV vary together
- Lower resolutions yield less stable estimates





Entropy

Conditional Variance



0.2

Shannon20



0.8



790 590 190 -10 0 0.2 0.4 0.6 0.8 1 Shanon25



1100

900

700

500

300

100

-100

0

02

0.4

0.6

Shannon SL1SIS05

1400

1100 800

500

200 -100

CV20

0.8

0.2

CV05

Uncertainty of the SIS estimations

- Lower entropies SIS estimates are more stable than SGS
- Also lower conditional variances dominate
- SIS entropies are less sensitive to grid resolution
- The width of the entropy interval changes less with grid resolution than in the case of SGS



Entropy

0.6

Shannon SL1SIS10

0.8

CV25

Plot of CV10 vs Shannon SL1SIS10



Plot of CV05 vs Shannon_SL1SIS05

2110

Plot of CV20 vs Shannon_SL1SIS20

0.6

0.8

0.4

Shannon SL1SIS20

500

300

100

-100

0 2

0.4





Conditional Variance

0.8



Slice2 - Representativity





Quantile-Quantile Plot







Statistics of Slice2 outputs

- SGS honors model distribution better than SIS
- MD type estimates less far from model distribution than in case of Slice1





Slice2 SGS QQ plots for pooled realizations and MD estimations

- The fits for SGS are reasonably good for the pooled realizations with small differences between resolutions
- MD type estimates are more sensitive to change of grid resolution then pooled realizations (lower heterogeneity)





Slice2 SIS QQ plots for pooled realizations and MD estimations

- Compared to SGS, the fits for SIS a less accurate
- For SIS grid resolution also matters at the level of pooled realizations
- The fit for MD type estimates is not that accurate compared to the pooled realizations





Slice2 MD type visualizations

- Better representativity of sample data set results in a more reliable spatial prediction
- Better reproduction of inner heterogeneities with SIS





Original image

SIS



CV SL

Uncertainty of the SGS estimations

- Stable estimates around data locations
- More areas with higher uncertainties than in case of SIS

Plot of CV SL2SGS05 vs Shannon SL2SGS05

0.6

0.4

Shannon SL2SGS05

• CV confirm entropies

0.2









Uncertainty of the SIS estimations

- Better connectivity of areas characterized by low uncertainties
- Lower entropies and conditional variances



Entropy

0.4

0.6

0.8













Overview

	SGS	SIS
Reproduction of the model distribution in highly heterogenous case	\checkmark	×
Reflecting high heterogeneities in space	\checkmark	×
Uncertainties related to high heterogeneities	×	\checkmark
Reproducing the model distribution in the low heterogeneity case	\checkmark	×
Reflecting low heterogeneities in space	×	\checkmark
Uncertainties related to low heterogeneities	×	\checkmark
Effect of grid resolution on reproducing heterogeneities	×	*



Summary

- Building a model that actually suits the data
- The measures of uncertainty are characteristic of the model, the simulation and its outputs rather than the studied process itself
- Statistics of pooled realizations match the model distribution better than the estimates derived from them
- However, estimates are inevitable for spatial assessment and for dinamic simulations