

Sequential Gaussian Simulation —using multi-variable cokriging

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Outline

- Motivation
- Methodology
- Case study --- Blackfoot data
- Conclusion
- Acknowledgements

Motivation

- A limitation of the deterministic method is the result generated has difficulty capturing the natural heterogeneity of reservoirs due to the smoothing effect.
- The sequential simulation technique provides a series of equal valid and possible realizations that reflect the distribution of reservoir properties.
- One of the key steps to generate a realization is to build the probability density distribution based on the conditional mean and covariance at each unsampled location.
- Heiskanen and Moritz (1967) and Dermanis (1984) showed that least square prediction is equivalent to a simple geostatistical system.
- Tarantola (2005) demonstrated that the least square problem can also be described as the posterior Gaussian probability density distribution.
- Hansen et al. (2006) expanded Tarantola's work to use two types datasets.

Methodology

$$P(m|a, b) = \text{const.} \exp\left[-\frac{1}{2} (\mathbf{m} - \boldsymbol{\mu}_{m|a,b})^T \boldsymbol{\Sigma}_{m|a,b}^{-1} (\mathbf{m} - \boldsymbol{\mu}_{m|a,b})\right]$$

where the conditional mean as

$$\boldsymbol{\mu}_{m|a,b} = \boldsymbol{\mu}_m + (\mathbf{G}\mathbf{C}_m)^T (\mathbf{G}\mathbf{C}_m\mathbf{C}^T + \mathbf{C}_d)^{-1} (\mathbf{d} - \boldsymbol{\mu}_d)$$

where the conditional covariance matrix

$$\boldsymbol{\Sigma}_{m|d} = \mathbf{C}_m - \mathbf{C}_m\mathbf{C}^T (\mathbf{G}\mathbf{C}_m\mathbf{C}^T + \mathbf{C}_d)^{-1} (\mathbf{d} - \boldsymbol{\mu}_d)$$

$$\mathbf{d} = \begin{bmatrix} \mathbf{a} \\ \mathbf{b} \end{bmatrix}, \mathbf{C}_d = \begin{bmatrix} \mathbf{C}_{aa} & \mathbf{C}_{ab} \\ \mathbf{C}_{ab} & \mathbf{C}_{bb} \end{bmatrix}, \boldsymbol{\mu}_d = \begin{bmatrix} \boldsymbol{\mu}_a \\ \boldsymbol{\mu}_b \end{bmatrix},$$

$\boldsymbol{\mu}_m$ and \mathbf{C}_m are the mean and covariance of target object.

➤ For multiple types of datasets $\mathbf{d} = \begin{bmatrix} d_1 \\ \vdots \\ d_n \end{bmatrix}, \mathbf{C}_d = \begin{bmatrix} \mathbf{C}_{d_1d_2} & \cdots & \mathbf{C}_{d_1d_n} \\ \vdots & \ddots & \vdots \\ \mathbf{C}_{d_1d_n} & \cdots & \mathbf{C}_{d_nd_n} \end{bmatrix}, \boldsymbol{\mu}_d = \begin{bmatrix} \boldsymbol{\mu}_1 \\ \vdots \\ \boldsymbol{\mu}_n \end{bmatrix}$

Methodology

➤ Rescaled Ordinary CoKriging (ROCK)

➤ We can extend rescaled ordinary cokriging from one to two secondary datasets :

$$\hat{u}_0 = \sum_{i=1}^n a_i u_i + \sum_{j=1}^m b_j (v_j - m_v + m_u) + \sum_{k=1}^p c_k (x_k - m_x + m_u)$$

➤ The weights are computed using the matrix equation:

$$\begin{bmatrix} \mathbf{a} \\ \mathbf{b} \\ \mathbf{c} \\ \mu \end{bmatrix} = \begin{bmatrix} C_{uu} & C_{uv} & C_{ux} & \mathbf{1} \\ C_{vu} & C_{vv} & C_{vx} & \mathbf{1} \\ C_{xu} & C_{xv} & C_{xx} & \mathbf{1} \\ \mathbf{1}^T & \mathbf{1}^T & \mathbf{1}^T & \mathbf{0} \end{bmatrix}^{-1} \begin{bmatrix} C_{u_0u} \\ C_{u_0v} \\ C_{u_0x} \\ 1 \end{bmatrix}$$

C_{ux} = well to 2nd seismic covariance,

C_{vx} = 1st seismic to 2nd seismic covariance,

C_{xx} = 2nd seismic to 2nd seismic covariance,

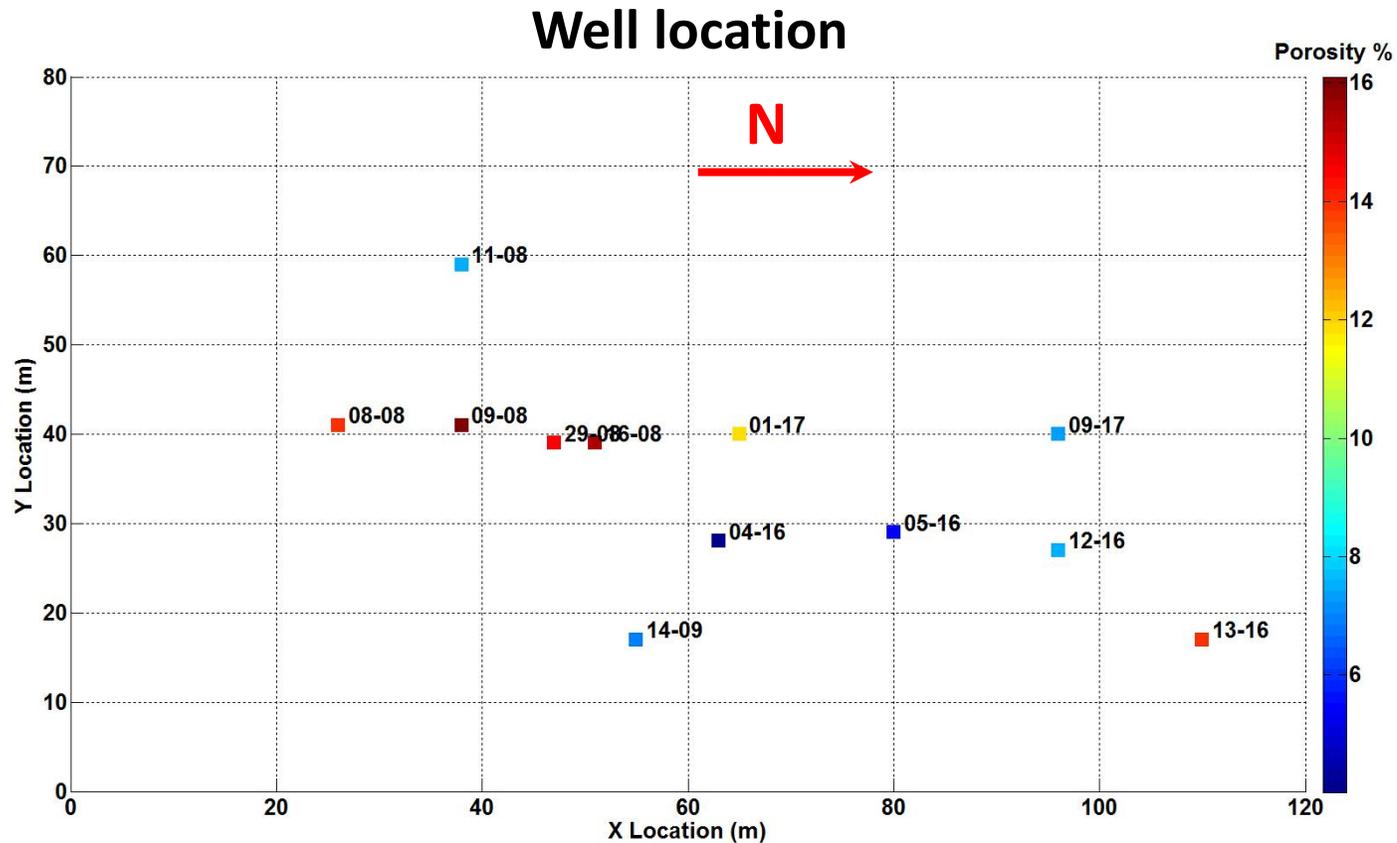
C_{u_0x} = unknown well to 2nd seismic covariance.

Methodology

➤ ROCK with n secondary datasets

$$\begin{bmatrix} w_1 \\ w_2 \\ w_3 \\ \vdots \\ w_n \\ \mu \end{bmatrix} = \begin{bmatrix} C_{uu} & C_{uv_1} & C_{uv_2} & \dots & C_{uv_n} & \mathbf{1} \\ C_{v_1u} & C_{v_1v_1} & C_{v_1v_2} & \dots & C_{v_1v_n} & \mathbf{1} \\ C_{v_2u} & C_{v_2v_1} & C_{v_2v_2} & \vdots & C_{v_2v_n} & \mathbf{1} \\ \vdots & \vdots & \vdots & \ddots & \vdots & \vdots \\ C_{v_nu} & C_{v_nv_1} & C_{v_nv_2} & \dots & C_{v_nv_n} & \mathbf{1} \\ \mathbf{1}^T & \mathbf{1}^T & \mathbf{1}^T & \dots & \mathbf{1}^T & 0 \end{bmatrix}^{-1} \begin{bmatrix} C_{u_0u} \\ C_{u_0v_1} \\ C_{u_0v_2} \\ \vdots \\ C_{u_0v_n} \\ 1 \end{bmatrix}$$

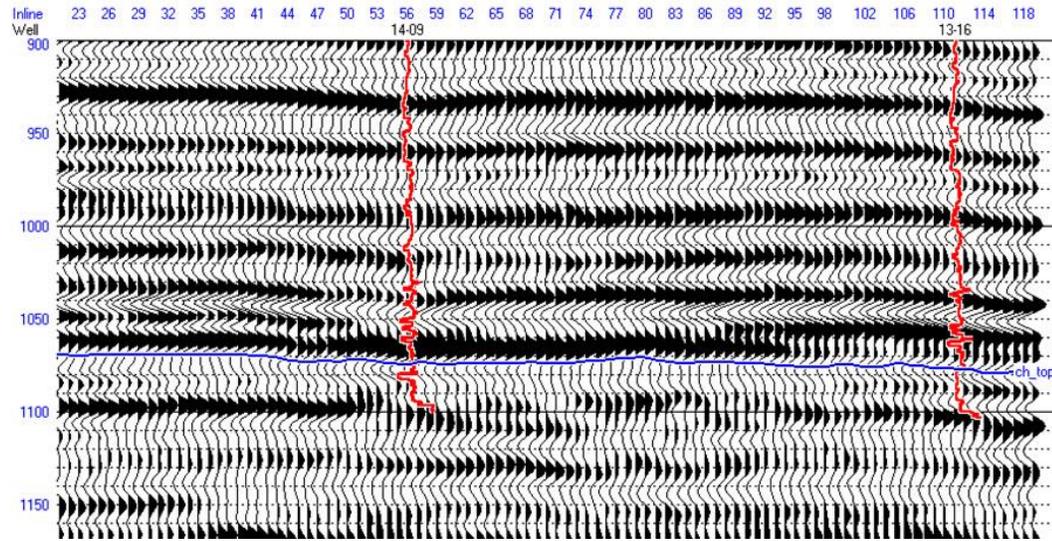
Case study --- Blackfoot



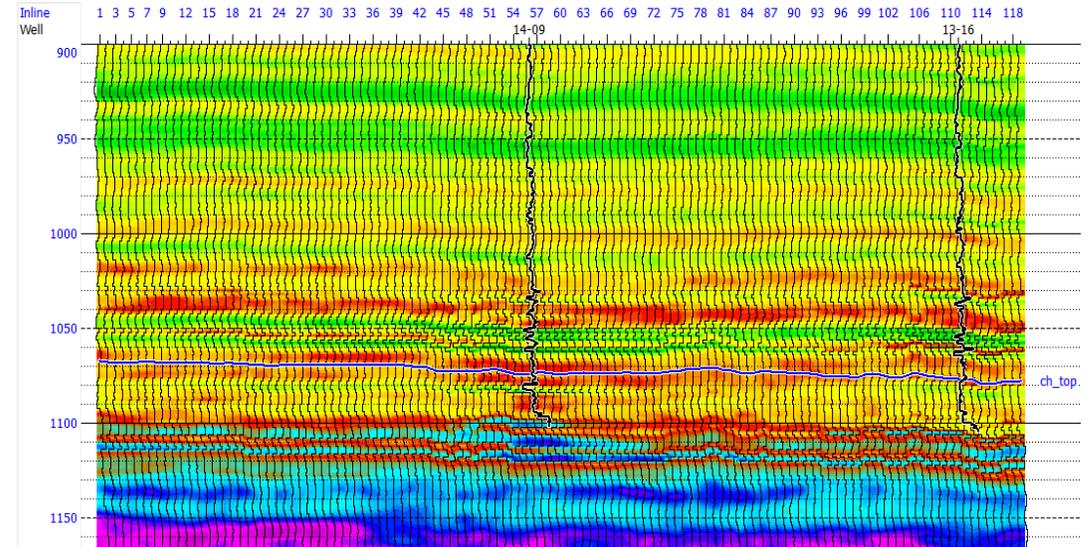
- 12 wells are located in the seismic survey area
- The color indicates the average porosity value of each well in the target zone

Case study

crossline 18 from the seismic volume

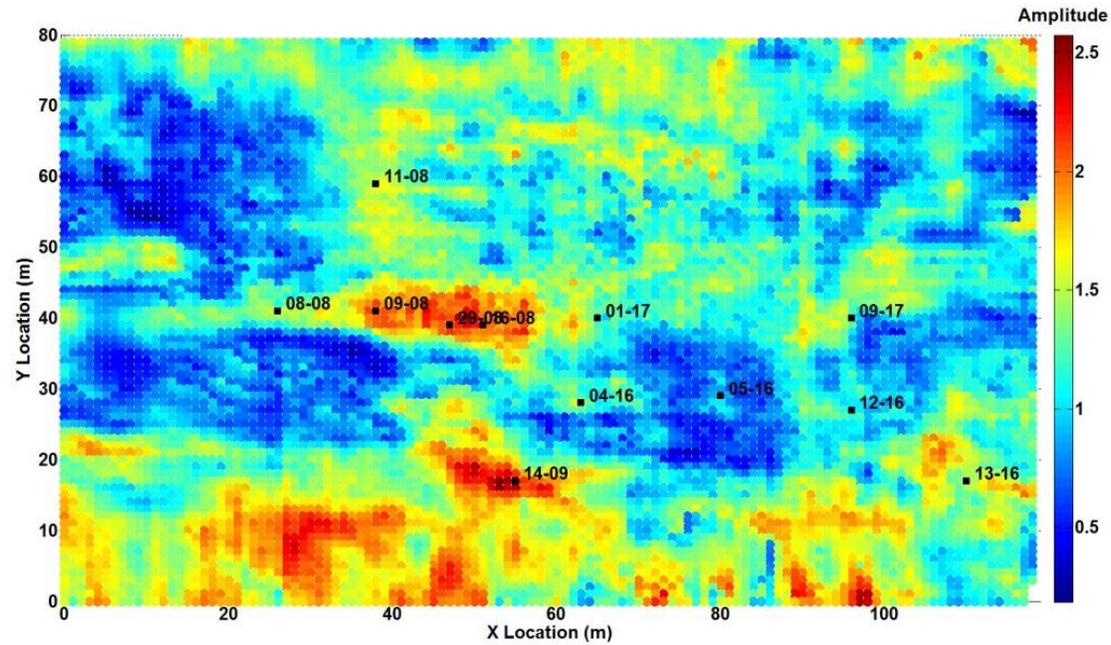


crossline 18 from the inverted volume

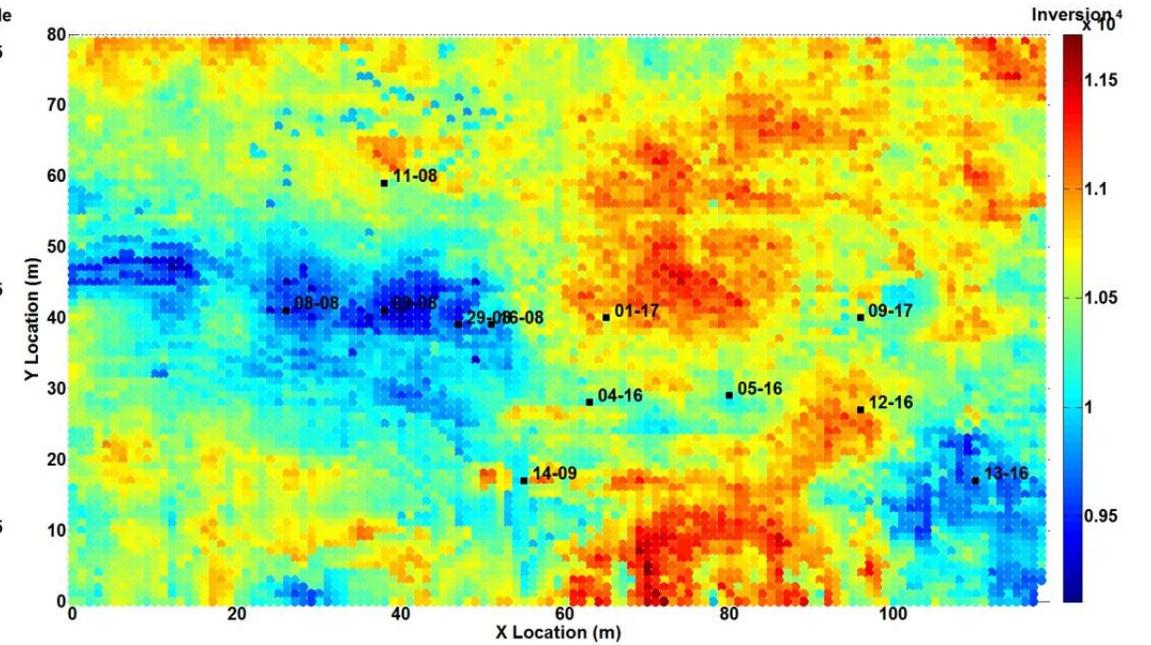


Case study

Amplitude of near-angle stack

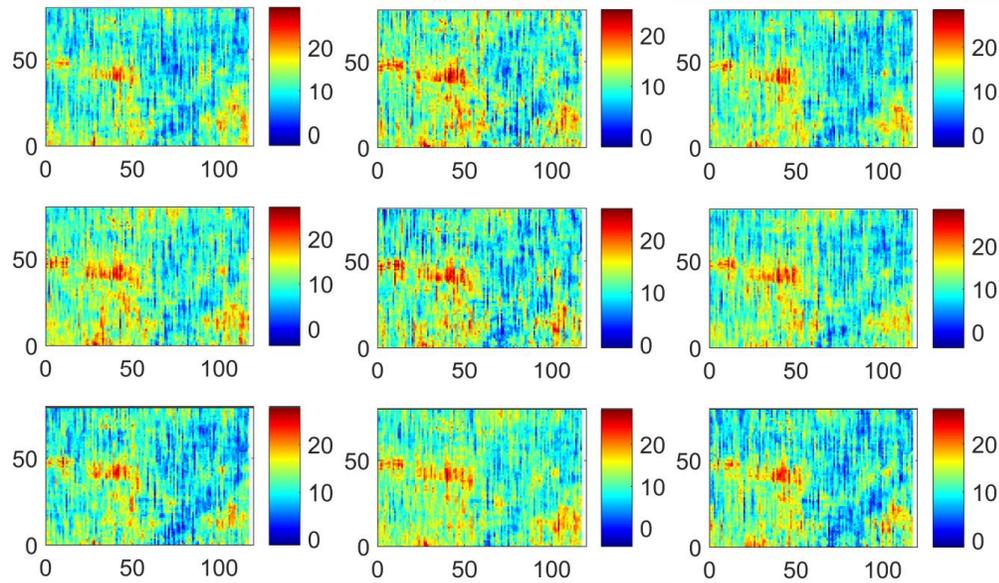


P-impedance inversion

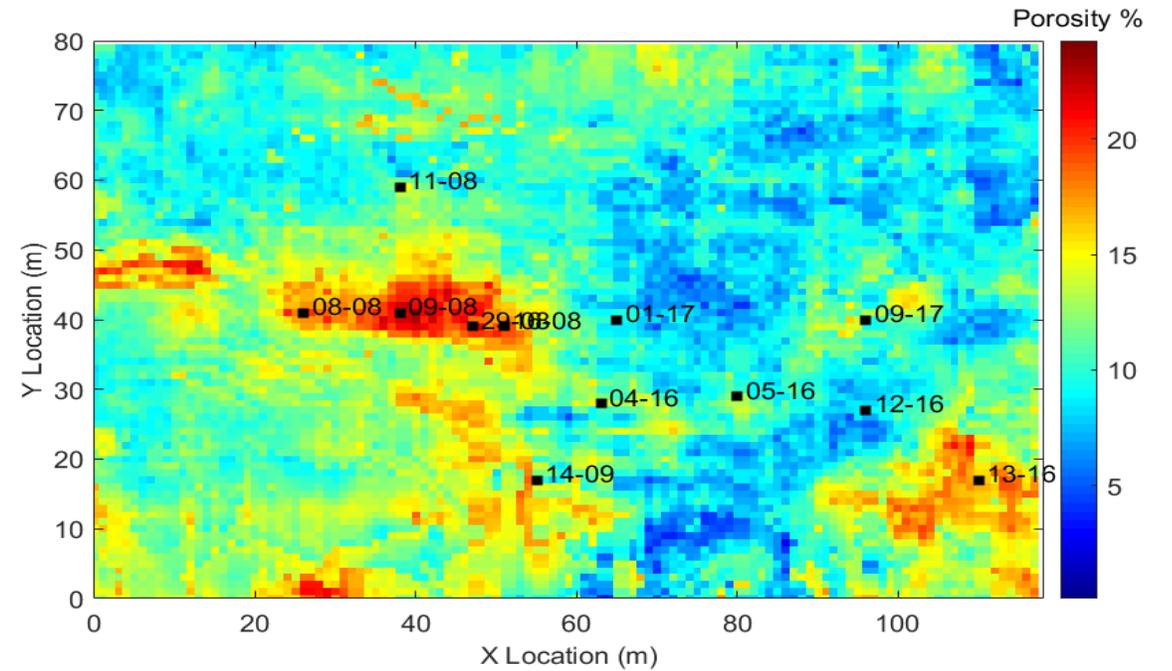


Result

9 realizations (SGS-extended ROCK)

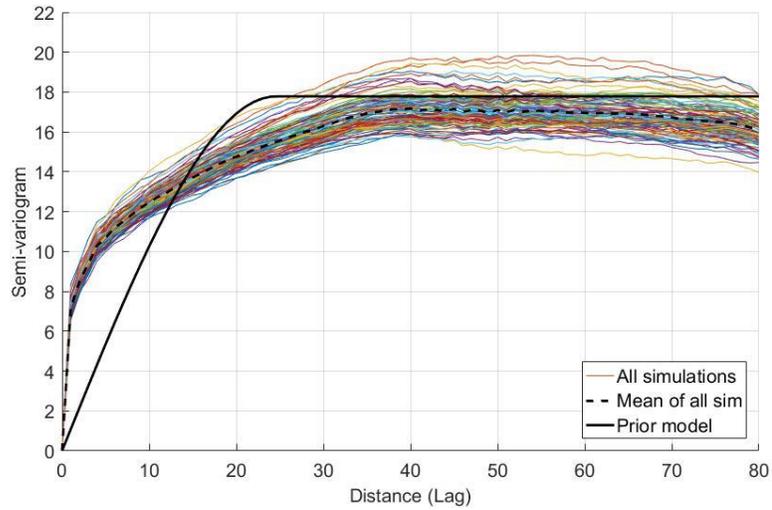


Porosity mean value map of all 100 realizations

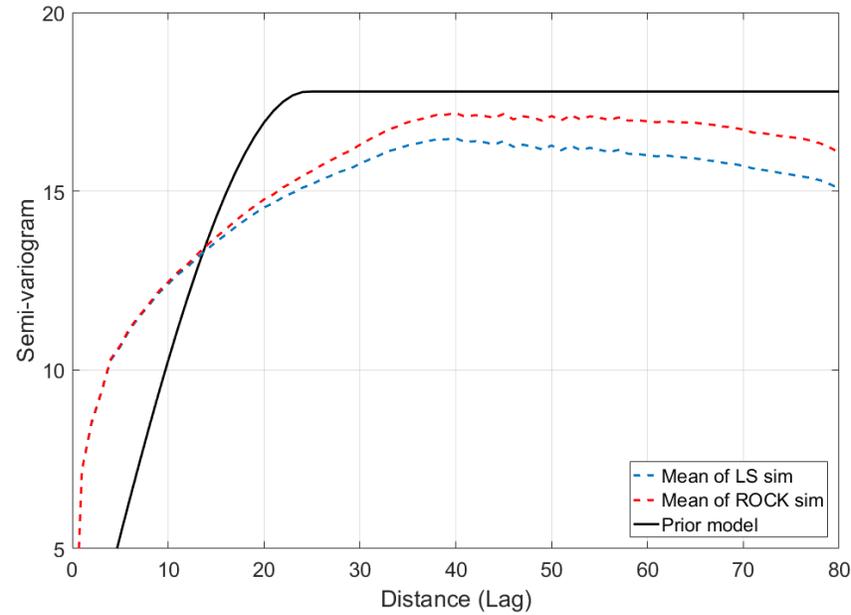
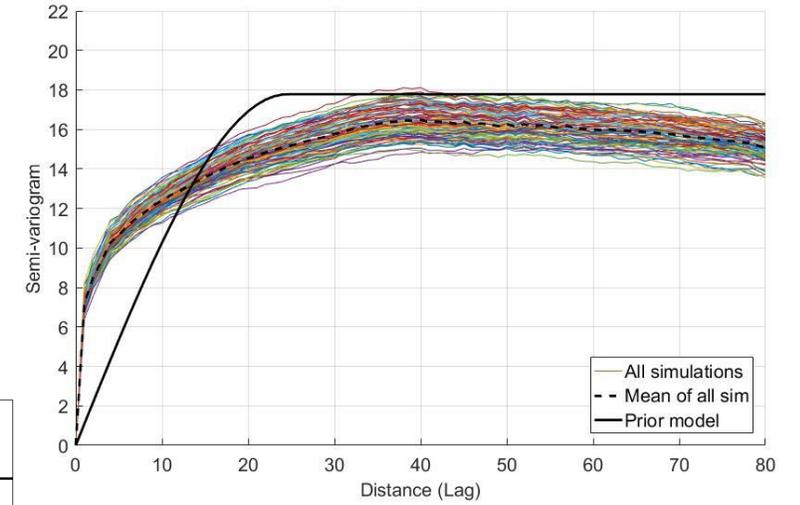


Comparison

Semi-variograms (SGS-extended ROCK)

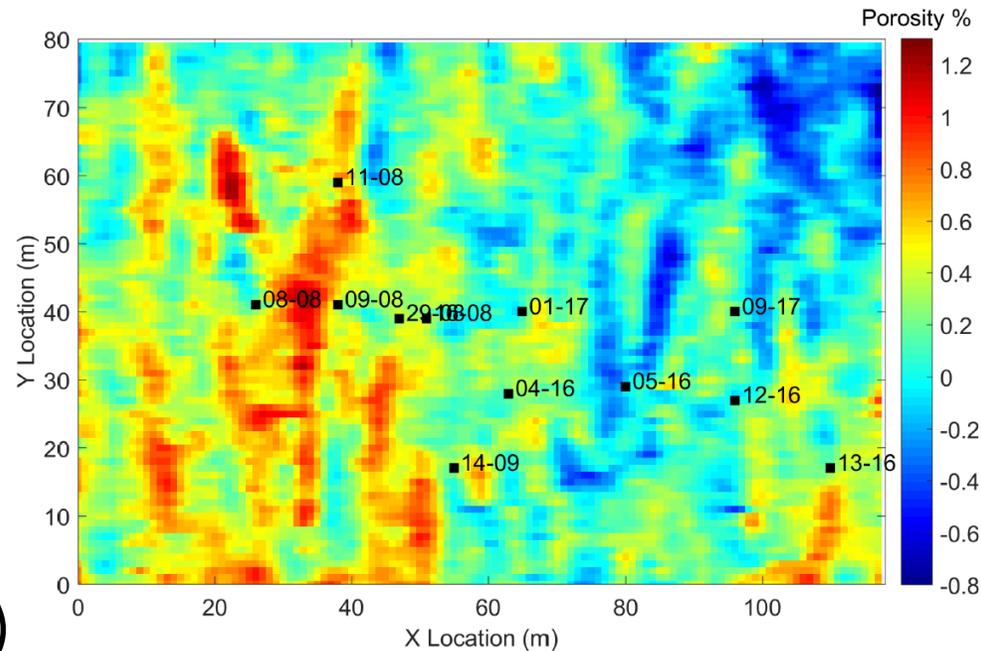


Semi-variograms (SGS-LS)



Comparison

- The difference of mean maps from 100 realizations between SGS-ROCK and SGS-LS



- Goovaerts (1998)

$$z_{RCK}(X) - z_{SCK}(X) = [W_{Primary}^{SCK} + W_{Secondary}^{SCK}] [m_{RCK}(X) - m_{Stationary}]$$

- The difference between extended ROCK and Least Square (SCK)

$$z_{ROCK}(X) - z_{SCK}(X) = [W_{Primary}^{SCK} + W_{Secondary1}^{SCK} + W_{Secondary2}^{SCK}] [m_{ROCK}(X) - m_{Stationary}]$$

Conclusion

- We presented an approach to implement the sequential Gaussian simulation (SGS) by extended Rescaled Ordinary CoKriging, which allows more than one secondary variable to participate in the process.
- The comparison of semi-variograms demonstrates that the realizations created by SGS-extended ROCK honor better to the prior information.
- The difference of mean maps shows that the SGS-Least Square is limited due to the global mean.
 - If local mean is higher than global mean, values are underestimated with SGS-LS.
 - If local mean is lower than global mean, values are overestimated with SGS-LS

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