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Bayesian inversion and visualization of hierarchical geostatistical models

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Geostatistical inversion methods estimate the spatial distribution of heterogeneous soil properties (here: hydraulic conductivity) from indirect information (here: piezometric heads). Bayesian inversion is a specific approach, where prior assumptions (or prior models) are combined with indirect measurements to predict soil parameters and their uncertainty in form of a posterior parameter distribution. Posterior distributions depend heavily on prior models, as prior models describe the spatial structure of heterogeneity. The most common prior is the stationary multi-Gaussian model, which expresses that close-by points are more correlated than distant points. This is a good assumption for single-facies systems. For multi-facies systems, multiple-point geostatistical (MPS) methods are widely used. However, these typically only distinguish between several facies and do not represent the internal heterogeneity inside each facies.

We combine these two approaches to a joint hierarchical model, which results in a multi-facies system with internal heterogeneity in each facies. Using this model, we propose a tailored Gibbs sampler, a kind of Markov Chain Monte Carlo (MCMC) method, to perform Bayesian inversion and sample from the resulting posterior parameter distribution. We test our method on a synthetic channelized flow scenario for different levels of data available: A highly informative setting (with many measurements) where we recover the synthetic truth with relatively small uncertainty invervals, and a weakly informative setting (with only a few measurements) where the synthetic truth cannot be recovered that clearly. Instead, we obtain a multi-modal posterior. We investigate the multi-modal posterior using a clustering algorithm. Clustering algorithms are a common machine learning approach to find structures in large data sets. Using this approach, we can split the multi-modal posterior into its modes and can assign probabilities to each mode. A visualization of this clustering and the according probabilities enables researchers and engineers to intuitively understand complex parameter distributions and their uncertainties.