A geostatistical parameterization for model-space reduction and Bayesian MCMC sampling

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Bayesian Markov chain Monte Carlo (MCMC) methods can provide robust information for geophysical model assessment and uncertainty analysis. Instead of focusing on the properties of a single 'best' model, the MCMC approach provides a framework for exploring the characteristics of many models that are consistent with measured data and any prior constraints. One critical challenge, however, is that MCMC methods are not readily adapted to high-dimensional problems with many thousands of parameters, such as the problem of solving for 2D or 3D models of spatially distributed geophysical properties. Sampling such a large parameter space is not tractable with current computational resources. Here, we propose to address this issue by carrying out the MCMC sampling in a reduced model-space domain, which naturally allows for substantially fewer parameter configurations to be tested. We consider the inversion of 2D profiles of airborne electromagnetic (AEM) data, which consist of thousands of densely spaced soundings along a flight line that are sensitive to the electrical resistivity structure to depths of ~100 m.

A typical image-based resistivity model along an AEM flight line has tens of thousands of parameters, but can often be divided into just a few spatially correlated domains associated with different lithologic units. Therefore, we parameterize the problem in terms of a geostatistical model with k different facies, where each facies is described by its mean resistivity, resistivity variance about the mean, and horizontal/vertical correlation lengths (Fig. 1). The MCMC algorithm samples the space of these $4*k$ underlying parameters that are consistent with the measured data and prior constraints, rather than tens of thousands of individual pixels in the image-based model. In order to compute the geophysical forward response and associated data likelihood function, however, an image-based model must be generated. To accomplish this, we use a conditional relationship that links each proposed set of underlying geostatistical parameters with a model of distributed resistivity values using sequential indicator simulation and sequential Gaussian simulation. A significant advantage to this approach is that we avoid sampling highly uncorrelated image-based parameter distributions that are unrealistic through the use of a geostatistical parameterization with implicit spatial constraints. The ensemble of models sampled by the MCMC algorithm not only contain the distribution of plausible geostatistical parameters constrained by the measured data, but also a large ensemble of individual image-based realizations of facies distributions and resistivity structure that can be evaluated in terms of model uncertainty and non-uniqueness.

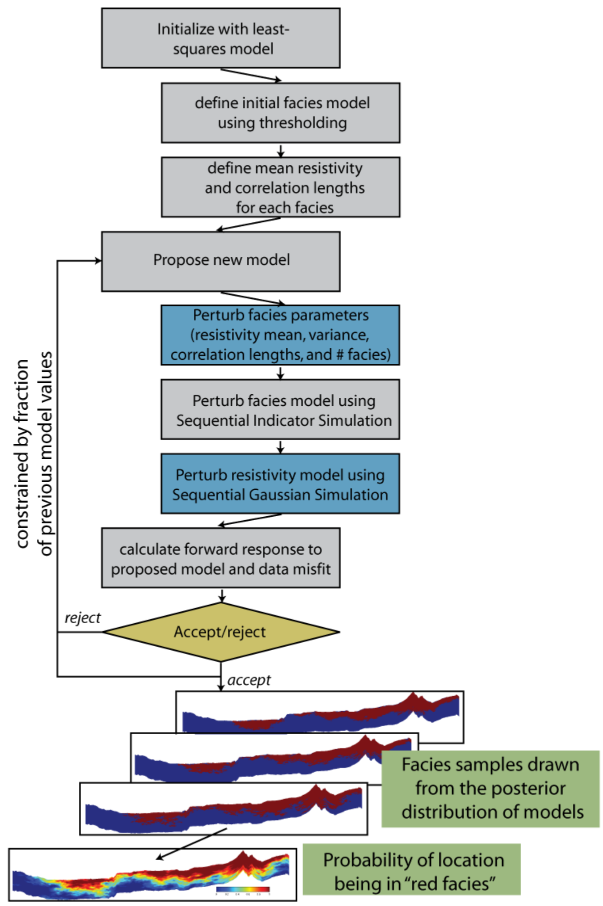

Figure 1. Flowchart for 2D Bayesian MCMC algorithm (top), with examples of resulting facies models drawn from the posterior distribution (bottom) that can be used to produce secondary products such as the probability of any location falling within a particular facies. Optional steps are shaded in blue.