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SITE CHARACTERIZATION USING JOINT RECONSTRUCTIONS OF DISPARATE DATA TYPES

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INTRODUCTION

Potential CO_2 reservoirs are often geologically complex and possible leakage pathways such as those created. Reservoir heterogeneity can affect injectivity, storage capacity, and trapping rate. Similarly, discontinuous caprocks and faults can create risk of CO2 leakage. The characteristics of potential CO_2 reservoirs need to be well understood to increase confidence in injection project success. Reservoir site characterization will likely involve the collection and integration of multiple geological, geophysical, and geochemical data sets. We have developed a computational tool to more realistically render lithologic models using multiple geological and geophysical techniques. Importantly, the approach formally and quantitatively integrates available data and provides a strict measure of probability and uncertainty in the subsurface. The method will characterize solution uncertainties whether they stem from unknown reservoir properties, measurement error, or poor sensitivity of geophysical techniques.

METHODOLOGY

The tool uses statistical theory and geophysical forward models to compute images of the subsurface reservoirs. It produces images that are consistent with disparate data types such as geostatistical trends of formation layers, geophysical logs, and surface or cross-borehole geophysical measurements. Joint reconstruction of these data results in subsurface models that are more realistic than those obtained conventionally. Our reconstruction method uses Bayesian inference, a probabilistic approach that combines observed data, geophysical forward models, and prior knowledge (e.g., geostatistical trends of layer correlation lengths, thicknesses and juxtaposition tendencies). The result is a sample of the distribution of likely lithology models that are consistent with the data collected. The method uses a Markov Chain Monte Carlo (MCMC) technique to sample the space of possible lithology models, including the shape, location and continuity of layers. Figure 1 shows a schematic diagram of the MCMC approach used for this study.

The approach that generates random lithology models (bottom of Figure 1) uses a geostatistical model to generate the "prior" spatial distribution of physical properties (resistivity, density, etc.) during each iteration in the MCMC process. Given that geophysical properties (such as electrical resistivity) tend to correlate with lithology or facies (rock categories with distinctive characteristics), we have employed a categorical geostatistical simulation approach. The model space is defined to consist of those combinations of voxel-level lithologic categories that are consistent with our prior spatial distribution. The main advantages of this approach are: (1) data are often categorical (e.g. lithologic descriptions), (2) geologic insight on the spatial characteristics of geologic systems (e.g., facies models) can be exploited, and (3) a very large proportion of the information known about the system can be represented very compactly using only a few lithologic categories.

The stochastic simulation code "TSIM" is used to propose random lithology models that honor prior data) TSIM (Carle, 1996; Carle et al., 1998) is a geostatistical simulation code that accurately honors the spatial variability model for multiple lithology problems. Each realization exhibits a similar pattern of spatial variability that is consistent with borehole data and geologic descriptions of the site. TSIM honors "hard" data, such as lithologic data at boreholes. "Soft" data, such as electrical resistivity logs, cone penetrometer data, or other forms of indirect data can also be used; in these cases, the relationship between the measured parameter and lithology is somewhat uncertain.

Additional capabilities of this approach are:

- Realizations can be generated that are similar to previous realization, as required by the MCMC algorithm.
- Prior knowledge of "nonstationarity" of lithology placement, e.g. information indicating that a certain lithology is more likely to occur in

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a certain area, can be considered.

MCMC is a proven technique that uses a random-walk type procedure to sample possible outcomes given all available data. A key advantage of the MCMC approach is that it automatically identifies alternative models that are consistent with all available data, and ranks them according to their posterior probabilities and associated confidences. In most geophysical applications, the inverse problem is substantially under-constrained and ill-posed. Thus, the search for a solution that is unique and possesses a high degree of confidence is generally impossible. Our approach makes use of prior information to sufficiently reduce the size of the space of feasible solutions in order to mitigate ill-posedness. The approach identifies competing models when the available information isn't sufficient to definitively identify a single optimal model. Another strength is that it can be used to jointly invert disparate data types such as those described earlier. The method also provides quantitative measures of the uncertainty of a generated estimate. Additional details of this approach can be found in Ramirez et al., 2005.

RESULTS

We have conducted a numerical experiment where disparate data types were used to infer the most likely lithologic model. The numerical model is based on a well-characterized site located at DOE's Savannah River Site (near Aiken South Carolina). At this site the lithology is known along a distal well, geophysical borehole logs are available and the overall geostatistical trends are well understood on the basis of core and outcrop studies. The site contains sand, silt and clay layers with minor gravel.

Using TSIM, we generated random lithologic realization that honored the core log and geostatistical trend data. One realization is shown in Figure 1 (top frame). The location of the distal well where the lithology is known is shown as a dark line along the right hand side of the figure. One realization, chosen as random, was designated as the "true" model (Fig.1, left frame, bottom row). Cross-well electrical resistivity data were calculated for electrodes located within a pair of wells (shown as small squares in Figure 1).

All the data (core logs from the distal well, cross well electrical resistivity data and geostatistical trends) were used to guide the search. The unknowns were the location and spatial trends of the lithologies within the domain. The results of the MCMC search are shown in the bottom row of Figure 1 as probability images. These images indicate the most likely location for each soil type. Note that there is reasonably good agreement between the probability images and the "true" model shown on the lower left corner of Figure1. The "true" model consists mainly of sand with a few thin clay and silt layers. The probability image corresponding to sand (white-yellow image, bottom row of Fig. 1) is mostly bright yellow; i.e. there is a high probability of sand at most locations. The white-blue and white-green images indicate the probabilities that clay and silt are present (respectively). These locations are also in good agreement with clay and silt locations in the "true model". Importantly, the study resulted in a new and more representative reservoir model that better explained the distribution of the contaminant plume.

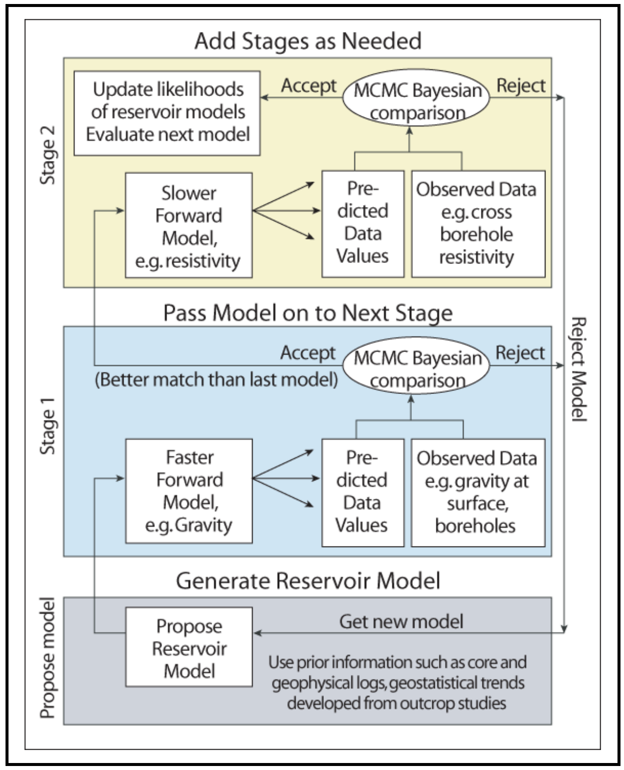

Figure 1. Schematic diagram of the MCMC approach used.

Figure 3 schematically illustrates how "soft" information such as a geophysical log can be incorporated with other data to further constrain the TSIM algorithm. Our approach establishes confidence levels for given lithology types. The left side of the figure shows an electric well log from the site. The vertical blue, green and yellow bands indicate the range of resistivity values associated with clay, silt and sand materials. These ranges were determined on the basis of expert judgement but can also be determined based on core studies or Bayesian time series analysis. Suppose that the resistivity curve is near the middle of the resistivity range for a silt (green band); a high confidence level would be assigned in this case because that is likely to be silt. Thus, the confidence level for silt at this depth would be 1.0 and 0.0 for silt and clay. If the resistivity falls along the edge between the green and yellow bands, we are quite confident that material at that location is not clay, but cannot decide whether it is sand or silt. In this case, the confidence level for clay would be 0.0, 0.5 for sand and 0.5 for silt. The rest of the electric log curve would be analyzed in similar ways. The diagram on the right side of Figure 3 schematically shows the confidence levels assigned to each lithology type based on the electric log data. The width of the colored section indicates the confidence level that each lithology (indicated by color) is present. The height of each section indicates the depth range associated with the confidence levels. This type of “soft” conditioning allows many kinds of data to be incorporated in the analysis. For example, results of geochemical or mineralogical analysis, other types of geophysical well logs, and the results of hydrologic pumping tests could be incorporated in this manner.

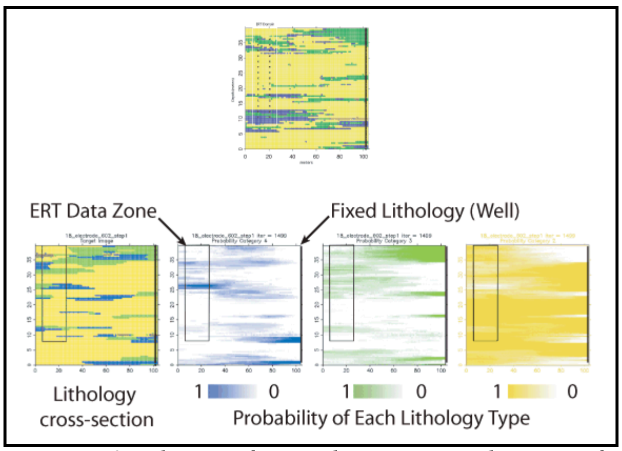

Figure 2. The top frame shows one realization of lithology. The bottom left frame shows the “true model. The remaning bottom frames show the probability that clay (white-blue image), silt (white-green image) and sand (white-yellow image) is present.

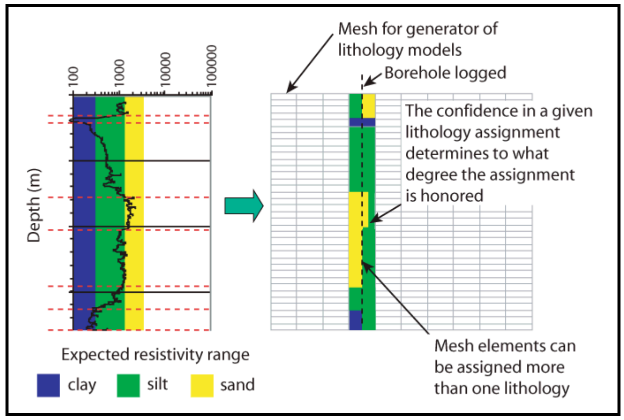

Figure 3. Schematic diagram showing how “soft” data such as a resistivity log (left side) is converted to lithology probabilities (right side of the diagram).

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