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Joint reconstructions of CO_2 plumes using a Markov Chain Monte Carlo approach

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Abstract

We describe a stochastic inversion method for mapping subsurface regions where CO_2 saturation is changing. The technique combines prior information with measurements of injected CO_2 volume, reservoir deformation and electrical resistivity. Bayesian inference and a Metropolis simulation algorithm form the basis for this approach. The method can a) jointly reconstruct disparate data types such as surface or subsurface tilt, electrical resistivity, and injected CO_2 volume measurements, b) provide quantitative measures of the result uncertainty, c) identify competing models when the available data are insufficient to definitively identify a single optimal model and d) rank the alternative models based on how well they fit available data.

We use measurements collected during CO_2 injection for enhanced oil recovery to illustrate the method's performance. The stochastic inversions provide estimates of the most probable location, shape, volume of the plume and most likely CO_2 saturation. The results suggest that the method can reconstruct data with poor signal to noise ratio.

Keywords: CO2, monitoring, inversion, resistivity, deformation

Introduction

Confidence in CO_2 storage is limited by the uncertainty in our subsurface knowledge. Subsurface CO_2 plume movement is often difficult to reconstruct due to uncertainties in reservoir architecture, distribution of porosity and permeability, and our ability to predict multi-phase fluid saturations. Similarly, the presence of heterogeneities and fast paths such as faults or abandoned wells that can create failure modes that might lead to CO2 leakage and shallow migration. Because natural reservoirs are complex, collection and formal integration of multiple geological, geophysical, and geochemical data sets and models can reduce or constrain key uncertainties and maximize our confidence in long-term CO_2 storage.

We have developed a stochastic computational tool to more realistically render CO_2 plume 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 plume models. The method will characterize solution uncertainties whether they stem from unknown reservoir properties, measurement error, or poor sensitivity of geophysical techniques. The rendering of plume geometry and character is highly robust, and new or existing data can often rapidly test predictions of the stochastic tool.

Methodology

Our reconstruction method uses Bayesian inference, a probabilistic approach that combines observed data, geophysical forward models, and prior knowledge to compute models of the subsurface CO_2 plumes. Joint reconstruction of the data results in plume models that are consistent with all available data. The result is a distribution of likely plume models. The method uses a Markov Chain Monte Carlo (MCMC) technique to sample the space of possible plume models, including the shape, location and CO_2 content of the plume. MCMC is a proven technique that uses a random-walk type procedure to sample possible outcomes given all available data. A detailed description of the application of the MCMC approach to plume reconstruction is found in Ramirez et al. (2005).

This approach is useful for a variety of subsurface problems such as geophysical inversion, data fusion, and reservoir fluid flow monitoring (water floods, steam injection, CO_2 floods). A key advantage of the approach is that it explicitly treats the non-uniqueness inherent in geophysical inversion. Alternative plume models are identified and then ranked based on how well they fit the data. It can incorporate disparate data types like structural geology maps identifying permeable layers and fracture zones, measurements of the injected CO_2 volume, reservoir deformation data, cross-borehole electrical resistivity, production data, geophysical logs, temperature measurements, tracer measurements, and gravity data.

Figure 1 schematically illustrates the data processing approach. The box labeled "Propose model" generates random plume models that honor prior knowledge. In our implementation, the following prior data are used: a) reservoir models (i.e., plumes are more likely to be located within permeable regions), b) the plume consists of a region of changing CO_2 saturation embedded within an otherwise unchanging volume, c) the changing region is composed of sub-regions that either overlap or are near each other, and, d) the CO_2 saturation value is in the range 0 – 1.0.

The box labeled *Stage 1* in Figure 2 indicates that the proposed plume model is used to predict reservoir deformation and that the predicted and observed deformation data are compared. The "MCMC Bayesian Comparison" box uses the Metropolis algorithm, Metropolis et al. [1], a randomized decision rule to accept or reject the proposed plume models according to their consistency with the observed data. This comparison always involves the current proposal and the last proposal that was deemed acceptable. If the current proposal fits the data better than the last accepted proposal, it is always accepted, and is passed to the box labeled *Stage 2* where a different type of data is considered, e.g., electrical resistivity. If *Stage 2* accepts the proposal using similar criteria as in *Stage 1*, the proposal has been determined to be consistent with all available data and becomes part of the distribution of accepted models. If the proposal is rejected by either *Stage 1* or *Stage 2*, the current proposal is discarded, a new proposal is randomly generated and the process repeats. Mosegard and Tarantola [2] originally described this staged reconstruction approach.

Most geophysical inversions are substantially under-determined, ill-posed and non-unique. Thus, the search for a solution that is unique and possesses a high degree of confidence is usually impossible. We believe that it is wise to use inversion methods that consider this non-uniqueness explicitly. The MCMC we describe automatically identifies alternative models and ranks them according to how well they fit the data thereby directly addressing the non-uniqueness problem.

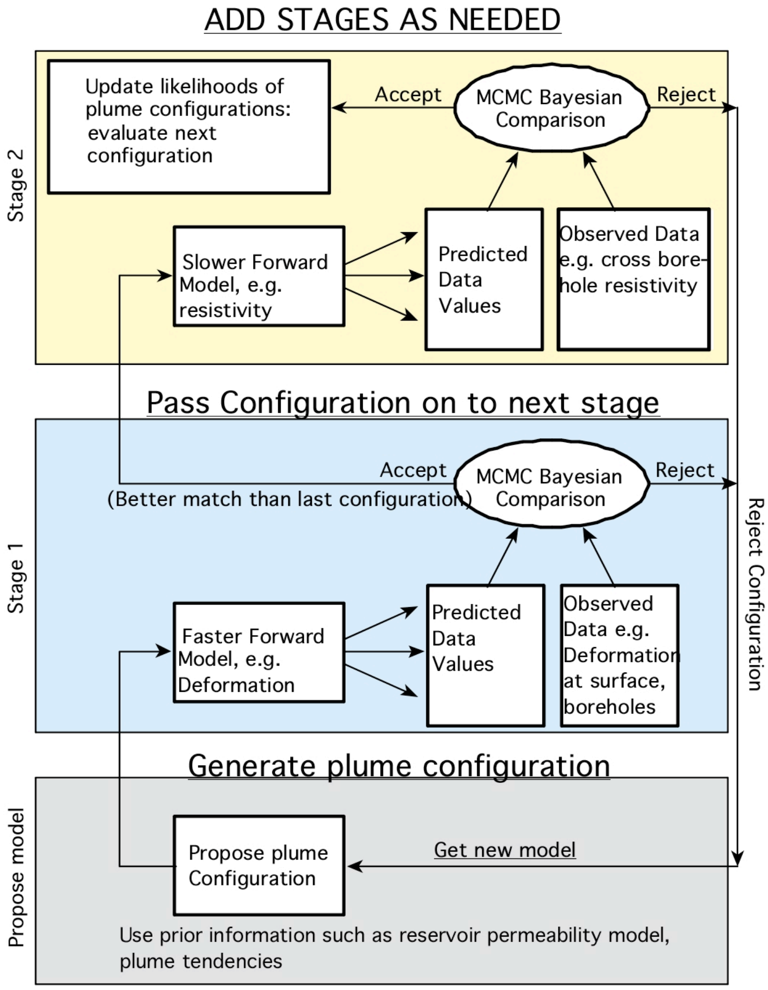

Figure 1 shows a schematic diagram that outlines the MCMC stochastic inversion approach.

Results

We have used this approach in many different applications, ranging from disease transmission to crustal velocity modeling to atmospheric release event reconstruction. As such, the MCMC approach can incorporate many different types of data as applied to many different kinds of problems. Below, we use field data collected before and during CO_2 injection to reconstruct CO_2 plume geometry within the target reservoir. The reservoir lies within the Salt Creek field, located near the southern tip of the Powder River Basin, Wyoming, U.S.A. The upper part of Figure 2 shows top and side views of the injection site. The block of interest is approximately 0.5 km by 0.5 km by 0.75 km. Seventeen abandoned steel wells were used as long (~710 m) electrodes to conduct cross-well electrical resistivity surveys.

The long electrodes provide a cost-efficient way of injecting electrical current within the reservoir to measure changes in pore fluid resistivity (Daily et al. [3]). The method requires no new wells nor does it affect injection/production operations. It produces data with low signal to noise ratios because only a small fraction of the injected current actually flows through the reservoir. At the Salt Creek site, most of the long electrodes only reach to the top of the reservoir thereby reducing the sensitivity to changes within the reservoir.

We first used a well-known, well-behaved, and regularized deterministic inversion algorithm (Morelli and LaBrecque, [4]) to process only the electrical data.

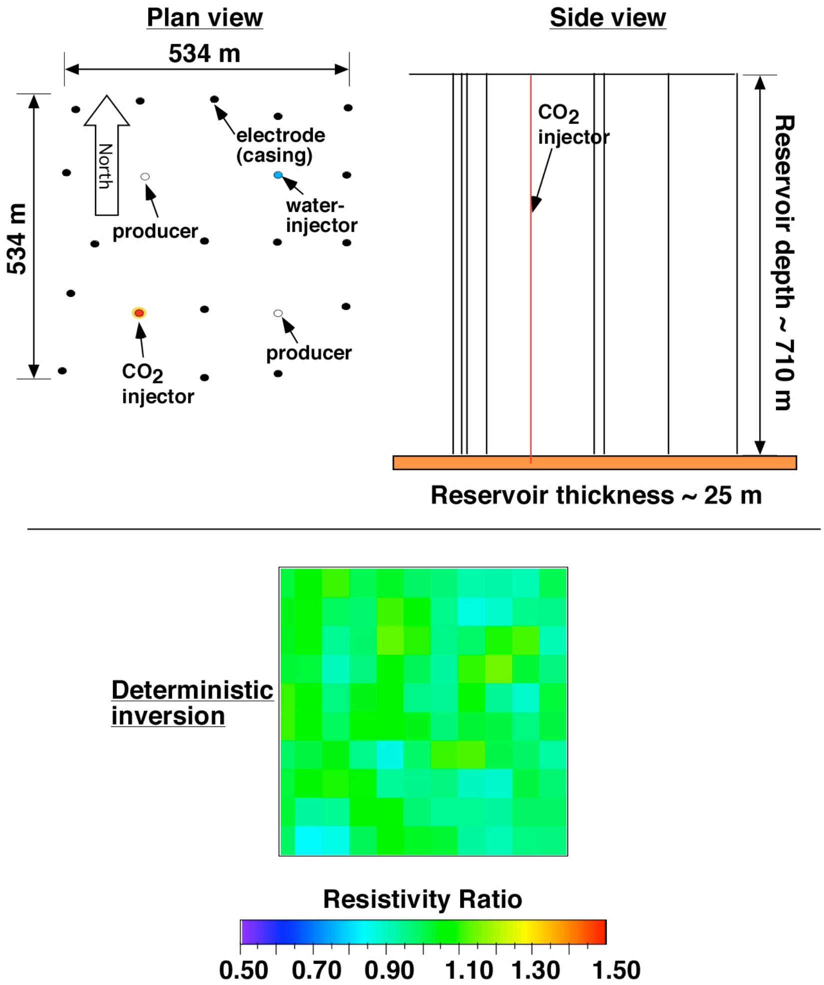

Figure 2. The top half of the figure shows plan and side views of the field site located within the Salt Creek field, Wyoming, USA. The bottom frame shows the results of a deterministic, time-lapse inversion after approx. 4600 m^3 of CO_2 had been injected).

The deterministic result is shown at the bottom of Figure 2. We only show a top view of the 3D block because this geophysical technique provides spatially constrained solutions only in horizontal model planes (Daily et al., [3]). Note that most of the tomograph is green, indicating a resistivity ratio (post-injection divided by pre-injection) near 1.0 (i.e., no change). Elsewhere, small changes are scattered throughout the image. We believe this uninformative results is due to the poor signal to noise ratio associated with the long electrode data.

We processed the same data electrical data using the MCMC approach. After an MCMC run is finished, it is necessary to verify that the accepted models are trustworthy, i.e., provide a statistically valid sample of the unknown posterior distribution (see Ramirez et al. [5] for details of the procedures discussed in this paragraph). We also need to distill the relevant information from the models in the posterior distribution so that the likely properties of the actual plume model can be identified. We use a clustering technique to extract this insight. As indicated earlier, our approach yields alternative models that are objectively ranked based on how well they fit the data.

Figure 3 shows the two most likely models found by the stochastic inversion. The model on the left is the most probable result, i.e., the result that is most consistent with all the available data. Synthetic model experiments suggest that such radially symmetric models are indicative of data with a very poor signal to noise ratio.

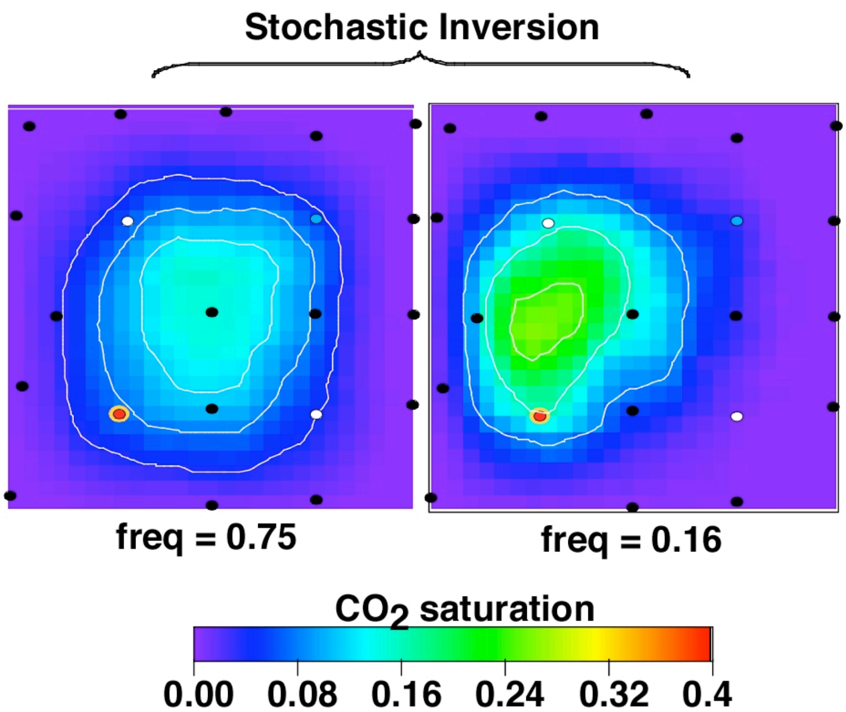

Figure 3 shows the results of a time-lapse stochastic inversion using the MCMC approach after approx. 4600 m^3 of CO_2 had been injected. The left frame shows the "best" model, i.e., the one that is most likely because it is most consistent with the data; the right frame shows the second best model found. The only observations used in this case were the cross-well resistivity data.

The model on the right of Figure 3 is the second most probable result. It shows an anomaly that spans the region between the injection and extraction wells and is more consistent with our expectations of a plume. These results suggest that the data contain a small amount of signal from the CO_2 plume that is nearly overwhelmed by the noise. We decided to additional measured data, injected CO_2 volume, to improve the confidence in the results. In other words, a new "stage" was added to the block diagram in Figure 1 such that the proposed plume models were evaluated for their consistency with the measurements of injected CO_2 volume.

Figure 4 shows the results obtained when the cross-well resistivity and injected CO_2 volume data were jointly reconstructed. The figure shows the most likely plume anomalies after 4600 and 6300 m^3 had been injected (approximately 2 weeks and 5 weeks after injection started). The left frames in Figures 3 and 4 show the effect of using the injected CO_2 volume; i.e., the radially symmetric anomaly (in Fig. 3) changes to an elongated anomaly (in Fig. 4) that connects the injection and extraction wells. Adding the injected volume data as an additional constraint enhances the effect of very small resistivity changes caused by the CO_2 in the reservoir. Also note that the probabilities for the images corresponding to 4600 and 6300 m^3 of CO_2 are 78% and 97% (respectively). As expected, confidence in the results improves as the volume of injected CO_2 increases and the measured signals become stronger.

Discussion

The improvement in rendering of the plume did not involve extensive repeat surveys. Rather, the addition of limited orthogonal data (in this case, injection volume) significantly constrained possible outcomes. Other kinds of constraints (e.g., production data, pressure or temperature data, first breakthrough of CO_2) may also constrain solution space. Our experience with the MCMC approach reveals that new data orthogonal to initial data often improves attribute prediction. It can also help illuminate which data provide the highest value in terms of reducing uncertainty.

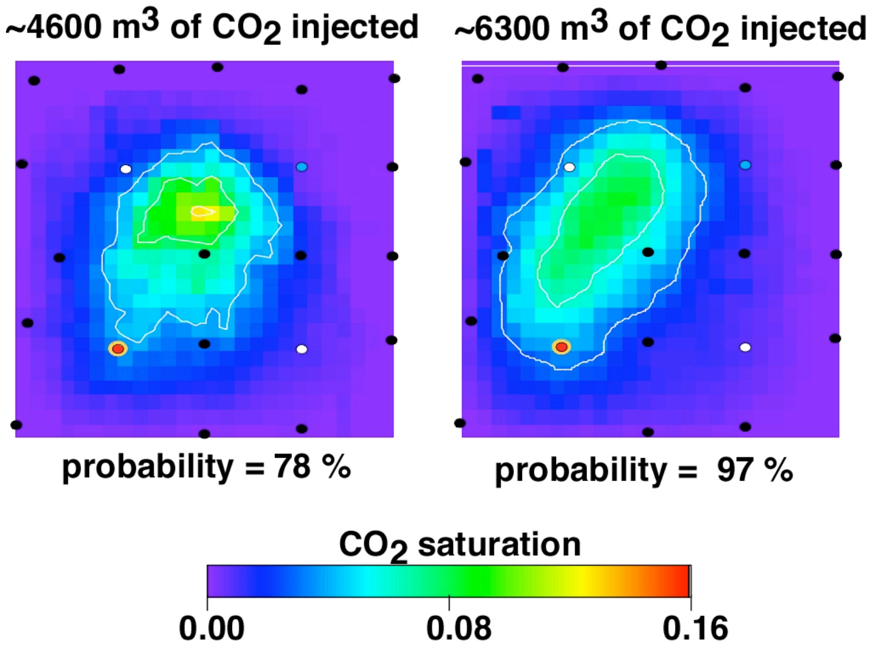

Figure 4 shows the results of two time-lapse stochastic inversions using the MCMC approach after approx. 4600 and 6300 m^3 had been injected. The images show the most likely model found, approximately two and five weeks (left and right frames, respectively) after injection.

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