FINAL REPORT

Time-Lapse Seismic Monitoring and Performance Assessment of CO_2 Sequestration in Hydrocarbon Reservoirs

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1. INTRODUCTION: BACKGROUND AND MOTIVATION

Carbon dioxide sequestration remains an important and challenging research topic as a potentially viable approach for mitigating the effects of greenhouse gases on global warming (*e.g.*, Chu and Majumdar, 2012; Bryant, 2007; Orr, 2004; Hepple and Benson, 2005; Bachu, 2003; Grimston et al., 2001). While CO_2 can be sequestered in oceanic or terrestrial biomass, the most mature and effective technology currently available is sequestration in geologic formations, especially in known hydrocarbon reservoirs (Barrufet et al., 2010; Hepple and Benson, 2005). However, challenges in the design and implementation of sequestration projects remain, especially over long time scales. One problem is that the tendency for gravity override caused by the low density and viscosity of CO_2. In the presence of subsurface heterogeneity, fractures and faults, there is a significant risk of CO_2 leakage from the sequestration site into overlying rock compared to other liquid wastes (Hesse and Woods, 2010; Ennis-King and Patterson, 2002; Tsang et al., 2002). Furthermore, the CO_2 will likely interact chemically with the rock in which it is stored, so that understanding and predicting its transport behavior during sequestration can be complex and difficult (Mandalaparty et al., 2011; Pruess et al., 2003). Leakage of CO_2 can lead to such problems as acidification of ground water and killing of plant life, in addition to contamination of the atmosphere (Ha-Duong, 2003; Gasda et al., 2004). The development of adequate policies and regulatory systems to govern sequestration therefore requires improved characterization of the media in which CO_2 is stored and the development of advanced methods for detecting and monitoring its flow and transport in the subsurface (Bachu, 2003).

One key area of focus within CO_2 sequestration R&D program has been the development of robust and cost-efficient monitoring technologies and protocols for tracking CO_2 plume migration in the subsurface. In this context, our research has been focused on fully integrating fluid flow and seismic data for monitoring injected CO_2 fronts by developing robust methods for reservoir characterization, coupled fluid flow modeling, including compositional and reactive processes and joint inversion of seismic and fluid flow data (Rey et al., 2012). For computational efficiency and suitability for large-scale field applications and inverse modeling, we have developed novel streamline-based compositional simulation of CO_2 sequestration including compressibility, compositional and geochemical effects (Datta-Gupta and King, 2007; Tanaka et al., 2013, 2014; Olalotiti-Lawal et al., 2016). To account for cross streamline mechanisms such as gravity and capillarity during CO_2 sequestration, we have introduced novel approaches based on orthogonal projection while maintaining the speed and intuitive appeal of the streamline models (Tanaka et al., 2014). We have exploited the analogy between streamlines and seismic ray tracing to develop efficient formalism for integrating time-lapse seismic and multiphase production data for high resolution subsurface characterization of hydrocarbon reservoir and tracking of the CO_2 plume (Watanabe et al., 2016). A key advantage of streamline modeling has been the analytic computation of the sensitivity of pressure, multiphase production and time lapse response to reservoir parameters (Kam et al., 2016; Rey et al., 2012). This makes high resolution joint inversion of time lapse seismic and multiphase production data feasible for routine application. Using field data from a hydrocarbon reservoir, we have demonstrated the advantages of incorporating time-lapse seismic variations for improved estimation of the permeability distribution, the pressure profile, the evolution of the fluid saturation, and reservoir swept volumes (Watanabe et al., 2016).

We have also continued to develop new and innovative approaches to seismic inversion and quantification of uncertainty in the results. The inversions are implemented using a reversible jump Markov Chain Monte Carlo (rjMCMC) framework, and an important advantage of this approach is that it allows for inference of the number of model parameters as well as parameter values. Our algorithm assumes that the model can be treated as a 1-D, plane-layered medium locally, and it then determines the number of layers and seismic velocity and mass density in each of those layers by minimizing misfit to seismic waveforms. Implementations include a novel approach to automatic well log upscaling, and inversions of seismic field data from the Norne Field in the North Sea and from the Shatsky Rise in the Pacific Ocean (Dadi, 2015; Dadi et al., 2016a; Dadi et al., 2016b; Zhu, 2016; Zhu and Gibson, 2016). Reliable quantification of uncertainty can be completed by carefully sampling the model space (Dadi, 2015; Zhu and Gibson, 2016). We have also made progress in exploring innovative approaches to numerical simulation of seismic wave propagation through media with complex, fine-scale heterogeneity. Conventional finite-difference schemes become prohibitively expensive when very finely sampled grids are applied to incorporate such heterogeneity, and reliable upscaling approaches for 3-D media are lacking. We have therefore explored the application of generalized multiscale finite element (GMsFEM) algorithms (Gibson et al., 2014; Gao et al., 2015a; Gao et al., 2015b). The approaches use numerical results from a fine-scale representation of model heterogeneity to compute basis functions that are applied to simulations on a coarse-scale grid. The result is an algorithm that can allow feasible computational results while retaining the influence of the fine-scale properties of the medium. The approach has strong potential for application to CO_2 sequestration problems, since fine-scale features often have strong influence on the movement and geometry of CO_2 distributions in the subsurface.

Our research effort has produced important insights about the feasibility of time lapse monitoring of CO_2 sequestration in hydrocarbon reservoirs. However, outstanding challenges remain for cost-effective tracking of CO_2 plumes and selection of seismic attributes to extend the applicability of our approach to a wider class of lithology and reservoir heterogeneities including faults and fractures and their impact on the areal and vertical migration pathways of the injected CO_2. These include aspects of flow simulation, seismic modeling, data assimilation and uncertainty quantification. Below we summarize the results of our research related to studies of fluid flow and seismic modeling in hydrocarbon reservoirs, highlighting results relevant to CO_2 sequestration. We then describe the problems that remain to be addressed for developing robust integrated characterization and monitoring schemes based on improved physical models and uncertainty estimates.

2. SUMMARY OF ACCOMPLISHMENTS

In this section we summarize our research related to seismic modeling and inversion, streamline-based compositional flow simulation and integration of the wave propagation and fluid flow models. In addition to 16 peer reviewed and several conference papers, one of the major accomplishments during the past three years has been the completion of a book documenting much of our research supported by the DOE Basic Energy Sciences and an industrial consortium on topics related to integrated subsurface characterization using static and dynamic data. The book, titled ‘Subsurface Fluid Flow and Imaging’ is scheduled for publication by the Cambridge University Press in August 2016 (Fig. 1).

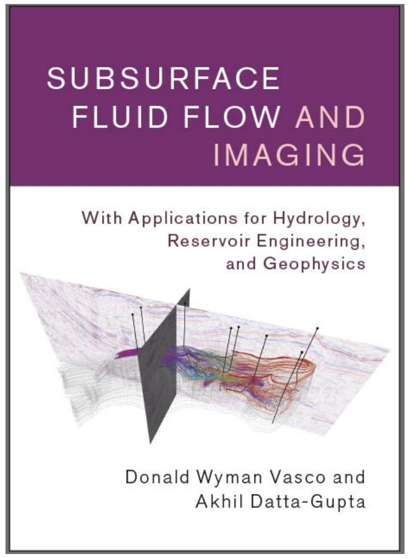

Fig. 1: Cover page of the book published by the Cambridge University Press (2016).

2.1 Streamline-based Forward and Inverse Modeling of CO_2 Sequestration

We have developed a comprehensive streamline-based flow simulator for compositional modeling of CO_2 transport in hydrocarbon reservoirs and saline aquifers. Our approach relies on the unique strength of streamlines in capturing small and large scale heterogeneity effects during CO_2 injection. Streamline simulators approximate three-dimensional fluid flow calculations by a sum of one-dimensional solutions along streamlines. The choice of streamline directions for the one dimensional calculations makes the approach extremely effective for modeling convection dominated flows in the reservoir. This is typically the case when heterogeneity is the predominant factor governing the flow behavior (Datta-Gupta and King, 2007).

A key underlying concept in streamline simulation is to decouple the effects of geologic heterogeneity from the physics of flow calculations. Mathematically, this is accomplished by utilizing the streamline 'time of flight' as a spatial coordinate variable (Datta-Gupta and King, 2007). The 'time of flight' is simply the travel time of a neutral tracer along streamlines. Using the streamline 'time of flight' as a spatial variable, we move to a coordinate system where all streamlines are straight lines and distance is replaced by the 'time of flight'. The impact of heterogeneity is embedded in the 'time of flight' and trajectory of the streamlines. The physical process calculations are reduced to one-dimensional solutions along streamlines. The streamlines are generally distributed in space with higher resolution than the underlying spatial grid, thus providing excellent transverse resolution. Saturation calculations along streamlines are decoupled from the underlying grid and can be carried out with little or no intrinsic time-step limitations. This can lead to significant speed up in computation time compared to conventional finite-difference or finite-element simulation.

Our streamline model is based on an iterative IMPES scheme and accounts for all relevant physical phenomena characteristic of CO_2 injection in hydrocarbon reservoirs as well as in saline aquifers: compressibility, gravity, capillary effects, phase behavior, mutual solubility, precipitation and formation dry-out effects (Tanaka et al., 2014; Olalotit-Lawal and Datta-Gupta 2016). To the best of our knowledge, this is the most comprehensive streamline-based CO_2 sequestration model to-date. Our approach incorporates compressibility effects by incorporating an ‘effective density’ that accounts for fluid expansion and contraction along streamtubes. Transverse fluxes such as gravity, capillarity and diffusion are accounted for using a novel orthogonal projection approach, leading to a step change in the applicability of the streamline simulation. Mutual solubility and precipitation-dissolution effects are included to account for well injectivity alteration during CO_2 injection. Comparisons between streamline simulation and a commercial compositional finite difference simulation results show excellent agreement in terms of pressure, phase saturations and component concentration at a fraction of the computational cost (Figs. 2 and 3).

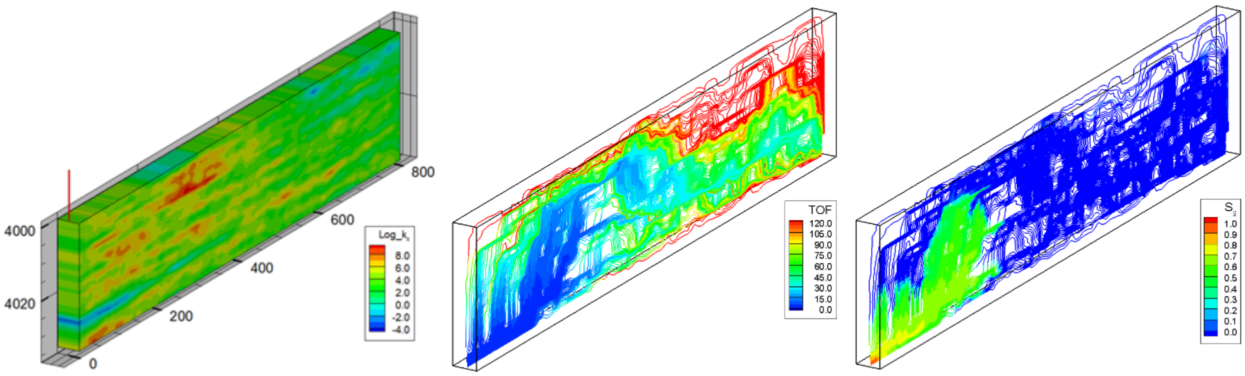

Fig. 2: (a) Heterogeneous 2D cross-section model showing logarithm of permeability distribution and CO_2 injection well (red line) (b) Streamline distribution with Time of Flight contoured along each streamline (c) Saturation of CO_2 rich phase near injector contoured along streamlines

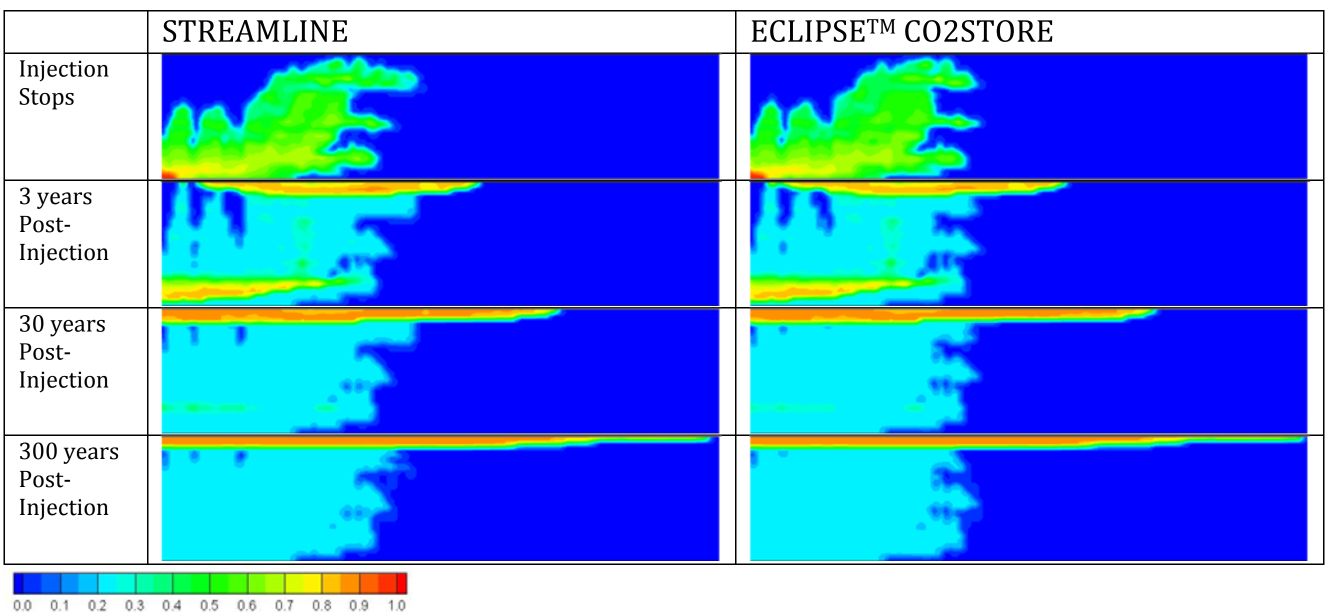

Fig. 3: Time Lapse progression of CO_2-rich phase saturation: Streamline Model (left panel) vs. Commercial Finite Difference Model (Right Panel).

For data inversion and model updating, we have introduced a novel semi-analytic approach to compute the sensitivity of the fluid saturation, time lapse seismic response and well bottom-hole pressure data with respect to reservoir properties for reconciling high resolution geologic models to flow and time lapse seismic data (Kam et al., 2016; Watanabe et al., 2016). The approach takes advantage of the streamline trajectories and yields results that are comparable to parameters sensitivities computed from adjoint methods with significant speed-up in computation. The bottom-hole pressure sensitivities can be easily integrated with other available data for a joint inversion of water-cut, pressure data and time-lapse seismic using high resolution geologic models. An iterative least squared method (LSQR) is used to minimize a penalized objective function that includes the data misfit and appropriate 'norm' and 'roughness' penalty terms to preserve the prior model characteristics during the inversion. We have demonstrated the power and utility of our proposed method using synthetic and field examples (Watanabe et al., 2016). The field data from the Norne field in the North Sea include production and injection information from 1997 to the end of 2006, and multiple sets of time-lapse seismic data for the same period (2003-2001, 2004-2003, 2006-2004). The production data are in the form of water, oil, and gas rates and bottom-hole pressures at the producers. The seismic data, which were processed externally, are available for the model calibration as near, mid, far, and full offset stacked 3D volumes of reflection amplitudes. Fig. 4 shows the updated permeability distribution in some selected layers in the Norne field after joint inversion of seismic and production data. The time lapse seismic data was instrumental in identifying some of the large scale variations in the permeability distribution because of the influence of reservoir pressure and saturation distribution on the seismic attributes. The updated permeability model is then used to study the performance of CO_2 injection and utilization for enhanced oil recovery and propagation of the CO_2 saturation plume.

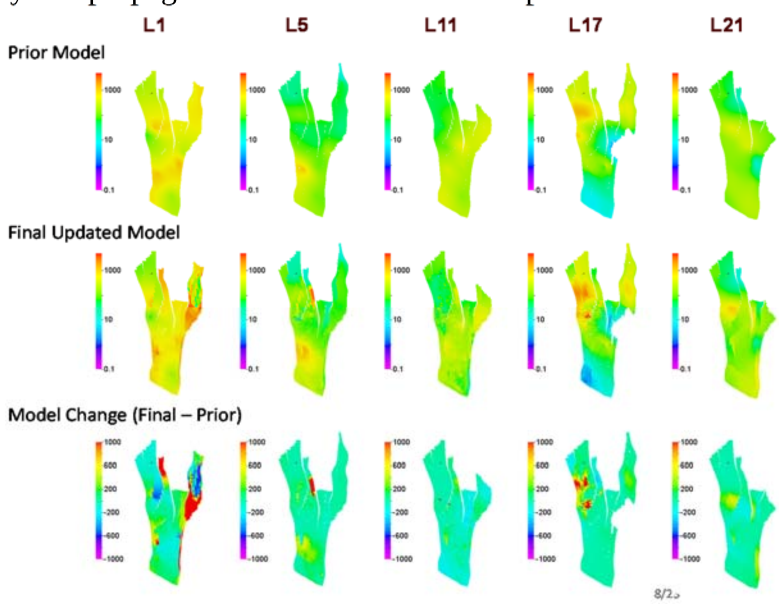

Fig. 4: Updated permeability field from joint integration of time lapse seismic and production data from the Norne Field.

2.2 Transdimensional Inversion of Seismic Field Data

Our recently completed research has successfully applied reversible jump Markov chain Monte Carlo (rjMCMC) methods to surface seismic data. One central aspect of this approach that makes it an attractive alternative for inversion is that it allows the model parameterization to be refined by the inversion itself rather than requiring specification of a fixed discretization of an earth model into a certain number of layers, for example. Instead, the number of layers is a parameter that is determined in the inversion process, as well as earth properties such as seismic impedance and mass density. Because the number of parameters defines the dimension of the model space, this is an example of a transdimensional algorithm. Furthermore, the rjMCMC algorithm is defined in a Bayesian framework that allows estimation of uncertainty in model parameters.

We have demonstrated the application of rjMCMC to automatic upscaling of well log data, including a rigorous analysis of uncertainty quantification (Dadi; 2014; Dadi et al., 2015). Reliable estimation of uncertainty requires careful attention to how model space is sampled in the Markov chain to avoid undersampling the space of potential models fitting data. In the past year, Biswas and Sen (2015) showed that rjMCMC can be applied to inversion of synthetic test data computed for a specific test model. We have applied the rjMCMC not only to synthetic test cases, but also to seismic field data from an oilfield to characterize the petroleum reservoir and to assess uncertainty (Zhu, 2016).

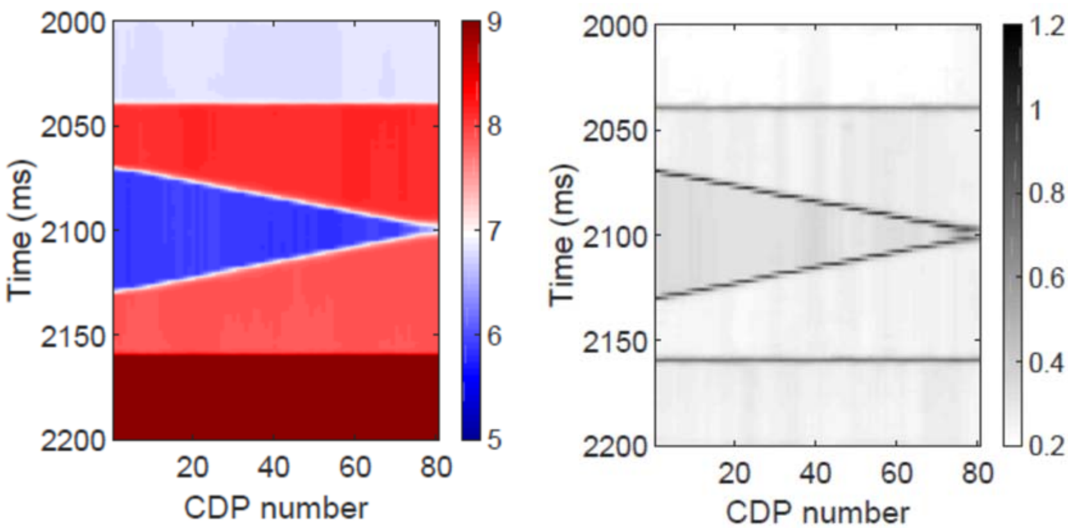

Fig. 5: Left: seismic impedance estimated by rjMCMC inversion. Right: uncertainty in estimated impedance.

Fig. 5 shows an example of inverted P-wave impedance (left) and the estimated uncertainty in that estimate (right). Here uncertainty is a measure of the standard deviation of the impedance value. Because the synthetic case allows straightforward estimation of model parameters, even though noise was introduced into the synthetic data, the impedance estimate very accurately maps the true values in the original model, with one exception. Specifically, the right end of the wedge shape in the center of the model should reach a sharp point, but it instead is blurred. This is an indication of the fundamental lack of vertical resolution of the seismic signals, which is an inherent consequence of the restricted frequency content of the data. The uncertainty estimate for this synthetic test case is uniformly low, except for at the boundary positions between layers. This results because a small change in boundary position still allows a reliable fit of the model predictions to data, but it causes the impedance value in the depth range near the boundary to oscillate between the values above and below the boundary. This is a potentially useful result, because calculating and visualizing this uncertainty can allow an automatic inference of the position of interfaces within an earth model.

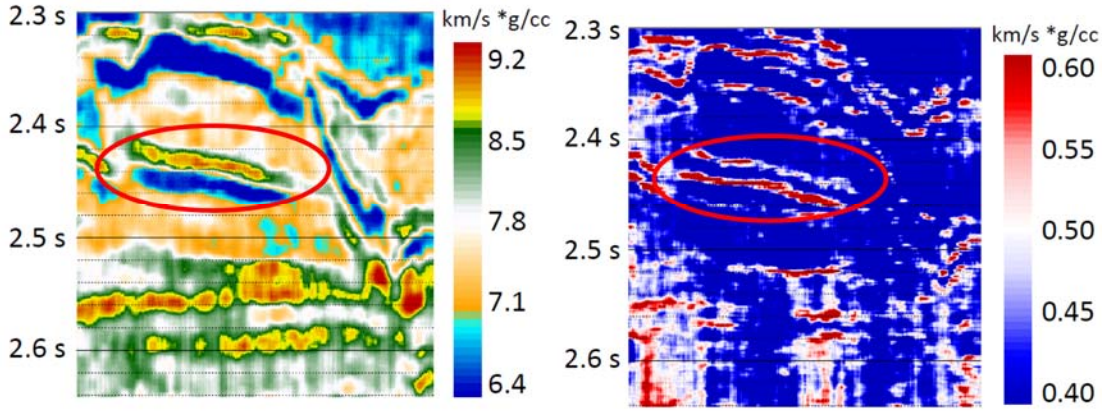

Fig. 6: Left: seismic impedance from inversion of seismic data from the Norne oil field. Right: uncertainty estimate for the impedance inversion.

This behavior is not restricted only to synthetic test cases. We applied the same rjMCMC algorithm to multioffset field data from the Norne field, which includes a hydrocarbon reservoir. The Norne field is located in the southern part of the Nordland II in the Norwegian Sea and is approximately 9km by 3km. A gas cap (25m) is mostly situated in the Garn formation, while the oil zone is mainly located in the Ile and Tofte formations which are shallow marine deposits with channelized sandstones. Fig. 6 compares the inverted P-wave impedance from near offset data and the associated uncertainty values. Red ellipses highlight the reservoir in this section. While there are more regions of high uncertainty, the reservoir feature in the inversion image is again associated with a boundary of a high uncertainty, which can help to identify reflecting surfaces. In addition, we compared inversion results to an industry standard inversion tool that is based on a deterministic algorithm. The result is similar, giving confidence to the inversion result, except that the rjMCMC result provides a more natural and rigorous uncertainty quantification.

2.3 Integrated Fluid Flow and Seismic Models: Fast Bayesian Inversion Algorithms

We have developed fast and robust Bayesian inversion algorithms using multilevel computational concepts. As for multilevel models, hierarchical models that approximate the detailed fine-scale solution are used. Furthermore, we have used multilevel Monte Carlo (MLMC) approach to approximate the expectation. In this method, more realizations are used at the coarser levels with inexpensive forward computations, and fewer samples are needed at the finer and more expensive levels. By suitably choosing the number of realizations at each level, a multilevel estimate of the expected values at much reduced computational efforts is obtained. Further, the use of MLMC jointly with multilevel Markov chain Monte Carlo (MLMCMC) methods is studied. The main idea of MLMCMC approach is to condition the quantities of interest at one level (e.g., at a finer level) to that at another level (e.g., at a coarser level). Specifically, for each proposal, the simulations at different levels are run to screen the proposal and accept it conditionally at these levels. As a result, samples from hierarchical posteriors corresponding to our multilevel approximations are obtained. These samples can be used for rapid computations within a MLMC framework.

In Efendiev et al. (2015), we applied this algorithm to two-phase flow and transport where we sampled the permeability field given the fluid production data. In Tan et al. (2014), we applied these algorithms to seismic inversion. In these numerical examples, the observed data are dynamic pressure responses at receivers placed at the surface. We sample the velocity field. The numerical result is shown in Fig. 7, where we compare the seismograms. We show that one can achieve a significant speed-up using multilevel Bayesian framework.

Instead of using MCMC an approximate Bayesian computation (ABC) method can be used and can be incorporated in different levels to reduce the computation cost and to produce an approximate solution by ensembling different levels. Approximate Bayesian Computation is a novel approach that allows for fast approximations where the likelihood does not have a closed form and it is expensive to compute the likelihood. Using the known data generating mechanism given the parameter, a data is generated and the parameter value is feasible when it is close enough to the observed data. The closeness in that approximating step controls the degree of approximation. In Guha et al. (2015) we have used the ABC in uncertainty estimation in inverse problems. We have obtained rigorous convergence results and shown numerically that these algorithms are efficient. These results are summarized in the Ph.D. thesis of Xiaosi Tan (2015).

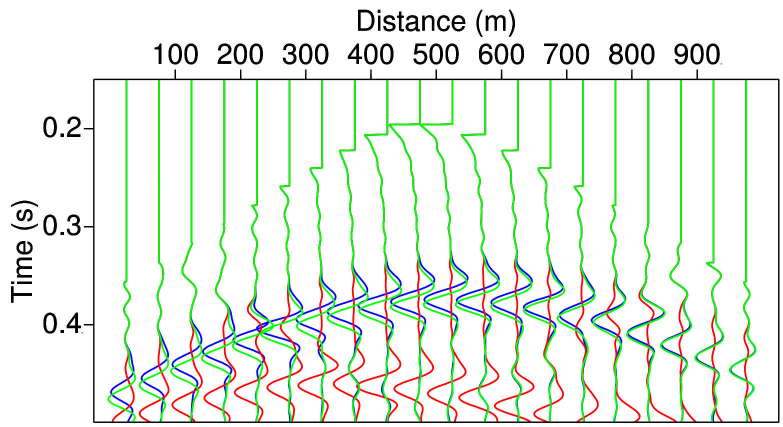

Fig. 7: Comparison of seismograms. Blue: reference solution; Red: initial guess; Green: Best fitted solution.

2.4 Integrated Inversion of 4-D Seismic and Fluid Flow Data for Monitoring and Assessment of CO_2 Sequestration: Outstanding Challenges

The research results discussed above demonstrate the advances we have made in seismic modeling, fluid flow modeling and the integration of the two for subsurface characterization and performance assessment of CO_2 sequestration in hydrocarbon reservoirs. However, outstanding challenges remain for cost-effective tracking of CO_2 plumes and selection of seismic attributes to extend the applicability of our approach to a wider class of reservoir heterogeneities and their impact on the areal and vertical migration pathways of the injected CO_2. These include aspects of flow simulation, seismic modeling, data assimilation and uncertainty quantification.

Geophysical monitoring methods do provide an indirect means of mapping the CO_2 plume. However, this mapping is generally based on a surrogate measure (e.g., amplitude, acoustic impedance etc.) and its projected response to fluid saturation changes based on a rock physics model which can have considerable uncertainty. In addition, the methods have varying degrees of spatial resolution, as well as cost of implementation. These "indirect" monitoring techniques can also be sensitive to geologic and site conditions, such as lithological heterogeneity, local wellbore and surface interferences (noise), and CO_2 plume volume. Additional constraints on such methods include technical and economic challenges if: (a) the CO_2 footprint is spatially extensive, (b) CO_2 is preferentially retained in thin high-permeability zones, or (c) CO_2 is moving in zones with insufficient sonic velocity contrast.

An underlying issue with CO_2 plume mapping through model-based integration of time-lapse seismic data is the requirement for a good *a priori* geologic reservoir description (static model) that is also conditioned by dynamic pressure and rate data from multiple wells. Taware et al. (2014) studied the problem of permeability estimation and plume delineation in a synthetic heterogeneous reservoir based on the inversion of bottom-hole pressure response at 1 injection and 3 monitoring wells. They found that a good match to observed pressure data for a calibrated model (Fig. 8, left panel) does not necessarily imply a good agreement between CO_2 saturation differences over time between the true model values and those estimated from the calibrated model (Fig. 8, right panel).

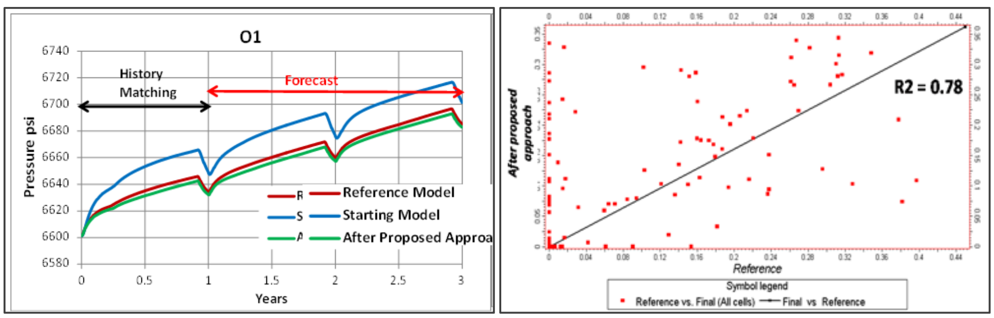

Fig. 8. Match of observed pressure data with calibrated model results (left panel), and comparison of saturation differences from true model with those predicted by the calibrated model (right panel), after Taware et al., 2014.

In practice, only a few inverse modeling studies can be expected to be performed during the course of a project because of data and computation needs. The confidence with modeling-based plume tracking is also likely to be impacted by issues of non-uniqueness (i.e., same pressure match leads to different plume images), resolution and uncertainty (i.e., good pressure match does not automatically imply a good saturation match) as noted above. Therefore, some of the potential areas of improvement with the modeling-based approach can be identified as: (a) better resolution and lower uncertainty in plume delineation through integration of time-lapse seismic and pressure monitoring data (b) increased frequency, i.e., (near) real-time conversion of pressure data to spatial plume extent, and (c) computational efficiency for routine field-scale applications.

There are also outstanding challenges that need to be addressed on the seismic modeling aspect. Many experiments have shown that seismic waves are sensitive to changes in the distribution of CO_2 in the subsurface, and that monitoring CO_2 flow through repeated, time-lapse seismic methods can provide critical insights for guiding sequestration efforts. These experiments have applied a wide range of acquisition geometries that often have widely different frequency ranges, including common seismic reflection processing results (Lumley et al., 2010; Lumley, 2010; Kazemeini et al., 2010; Ma and Morozov, 2010; Grude et al., 2014), Crosswell and vertical seismic profile (VSP) experiments (Harris et al., 1995; Daley et al., 2007; Cheng et al., 2010; Huang et al., 2008; Ajo-Franklin et al., 2013), and passive seismic data (Verdon et al., 2010; Paap et al., 2014; Gassenmeier et al., 2015). Recent developments have also explored the application of seismic interferometry methods to measure changes in complex scattered seismic waves in VSP data (Zhou et al., 2010; see also Khatiwada et al., 2009).

Nonetheless, CO_2 subsurface flow is controlled by complex geological features with broad ranges of horizontal and vertical scales that vary widely depending on geological properties of the sequestration site. For example, at the Cranfield location, CO_2 is injected into the Tuscaloosa Sandstone that is approximately 20m thick, with width of flow units typically less than 200m (Hovorka et al., 2013). In contrast, at the Sleipner sequestration site, the Utsira Sand Formation has a thickness of 200m, with important permeability barriers that are 1m in thickness (Chadwick et al., 2014). Given these complexities, reliable and quantitative analysis of both well data and seismic data with flow and seismic imaging methods faces significant challenges in completing integrated studies.

Some of these challenges in providing well-constrained, quantitative results are demonstrated by recent published analyses providing inconsistent and sometimes contradictory conclusions. For example, Xue et al. (2009) suggested that in many cases, it will be possible to detect volumes of CO_2 as low as 2500 to 1000 tons, in layers as thin as 1m. However, they also find that it will be difficult to detect changes in CO_2 saturations at levels above ~20%. Another important problem is how the distribution of CO_2 affects the seismic response, because there are differences in expected behavior if the CO_2 is uniformly distributed through the pore fluids or if it is irregularly distributed ("patchy") (Caspari et al., 2015; Pevzner et al., 2013). Other challenges result when the formation is particularly stiff, heterogeneous or at large depths (Gendrin et al., 2013).

These examples suggest two broad challenges remaining for routine application of seismic monitoring of CO_2 sequestration efforts. First, rigorous analysis of conditions under which changes in CO_2 saturations can be detected in settings with complex, fine-scale heterogeneity will provide improved guidance for integrating seismic data into sequestration monitoring. Such results can help to resolve some of the previously contradictory or ambiguous conclusions. We propose to address this problem by developing fast and efficient numerical modeling approaches applying numerical homogenization techniques (Gao et al., 2015) that will allow more reliable and accurate simulations of seismic data based on fine-scale geological descriptions of a sequestration site than are available with conventional approaches. The second general area is the development of improved models for relating both fluid saturations and stress changes to seismic response. In this area, we will extend previous research results described above (Gibson and Gao, 2015) to develop simpler, approximate expressions that will facilitate analysis of seismic amplitude variation with offset (AVO).

In addition to the unresolved issues in seismic and fluid flow modeling, challenges remain in the area of integrated inversions and uncertainty assessments. Uncertainty is inherent in dynamic reservoir modeling because of several factors, the primary ones being the uncertainty in geologic models, errors in forward modeling and data noise. The uncertainty in reservoir parameters is translated into uncertainty in reservoir performance for CO_2 sequestration that will impact the economic and operational risk analysis. In the context of the Bayesian inversion, the solution to the inverse problem is the posterior probability distribution itself. Therefore, the problem of uncertainty quantification is closely tied to the correct sampling of multiple reservoir models from the posterior distribution (Efendiev et al., 2008; Ma et al., 2008; Mondal et al., 2010). Such sampling is nontrivial because the posterior distribution is defined on a high dimensional space and is not known in a closed form. Furthermore, the posterior distribution can be both non-Gaussian and multimodal. This makes rigorous sampling from the posterior distribution extremely computationally demanding. Another challenge is the diverse forms of fluid flow and seismic data that can be potentially conflicting, particularly because of the interpretative nature of the seismic data. We plan to explore the use of multi-objective differential evolution Markov Chain Monte

Carlo (MCMC) algorithms for probabilistic integration of diverse data types that are available in hydrocarbon reservoirs. Use of fast flow simulation for rapid likelihood computation and also the appropriate choice of proposals in MCMC for higher acceptance and faster convergence will be critical to the practical feasibility of our approach.

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