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Detection of potential leakage pathways from geological carbon storage by fluid pressure data assimilation

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ABSTRACT

One of the main concerns of geological carbon storage (GCS) systems is the risk of leakage through "weak" permeable areas of the sealing formation or caprock. Since the fluid pressure pulse travels faster than the carbon dioxide (CO_2) plume across the storage reservoir, the fluid overpressure transmitted into overlying permeable formations through caprock discontinuities is potentially detectable sooner than actual CO_2 leakage occurs. In this work, an inverse modeling method based on fluid pressure measurements collected in strata above the target CO_2 storage formation is proposed, which aims at identifying the presence, the location, and the extent of possible leakage pathways through the caprock. We combine a three-dimensional subsurface multiphase flow model with ensemble-based data assimilation algorithms to recognize potential caprock discontinuities that could undermine the long-term safety of GCS. The goal of this work is to examine and compare the capabilities of data assimilation algorithms such as the ensemble smoother (ES) and the restart ensemble Kalman filter (REnKF) to detect the presence of brine and/or CO_2 leakage pathways, potentially in real-time during GCS operations. For the purpose of this study, changes in fluid pressure in the brine aquifer overlying to CO_2 storage formation aquifer are hypothetically observed in monitoring boreholes, or provided by time-lapse seismic surveys. Caprock discontinuities are typically characterized locally by higher values of permeability, so that the permeability distribution tends to fit to a non-Gaussian bimodal process, which hardly complies with the requirements of the ES and REnKF algorithms. Here, issues related to the non-Gaussianity of the caprock permeability field are investigated by developing and applying a normal score transform procedure. Results suggest that the REnKF is more effective than the ES in characterizing caprock discontinuities.

1. Introduction

In the last decades, geological carbon storage (GCS) has been identified as a technology of great potential for reducing anthropogenic emissions of carbon dioxide (CO_2) in the atmosphere. However, while technically feasible, GCS must be carefully evaluated with respect to environmentally threatening side effects, such as the leakage of CO_2 through sealing formations or caprock. When CO_2 is injected underground it displaces the resident fluid in the target geological formation, which, in the case of deep aquifers, is constituted mainly by high-density saline water, or brine. If brine and/or CO_2 find a pathway through the caprock, they migrate into overlying formations, which may lead to deteriorating the quality of shallow fresh water resources [1]. In particular, CO_2 can produce pH changes of groundwater resources by increasing the concentration of carbonates, which can consequently influence dissolution and sorption of minerals and hazardous trace metals [2,3].

The 2005 report of the Intergovernmental Panel on Climate Change [4] provided a list of potential CO_2 leakage pathways: (1) "weak" areas of the caprock (permeable areas), where CO_2 breaks into the caprock if capillary entry pressure is exceeded; (2) faults and fractures; and (3) poorly completed and/or abandoned wells. In order to monitor the migration of the CO_2 plume different techniques have been proposed. The US Department of Energy [5] classifies these techniques into three main groups: (I) atmospheric monitoring techniques, (II) near-surface monitoring techniques, and (III) subsurface monitoring techniques. From this perspective, Seto and McRae [6] highlighted the importance of developing model-based framework for risk-based monitoring design prior to large scale deployment of GCS. These frameworks are crucial to ensure safe CO_2 storage by gaining insight in site-specific processes, thus reducing uncertainties and allowing for the formulation of appropriate plans to reduce risk.

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Measuring fluids pressure is a key component of subsurface monitoring (Group III). Since the fluid pressure pulse travels faster than the CO_2 plume across the storage reservoir, leakage of brine through possible "weak" areas of the caprock into overlying permeable formations should be identifiable sooner than CO_2 leakage by measuring even small and localized fluid pressure variations in these formations. Fluid pressure changes can be detected, for example, by pressure-monitoring wells [5] or four-dimensional (4D) time-lapse seismic data [7–9].

To date, a number of studies related to monitoring pressure changes in observation wells have been published. Chabora and Benson [10] presented a method to assess the usefulness of subsurface pressure monitoring based on the correlation between calculated pressure changes and a proposed detection factor. Similarly, Zeidouni et al. [11] developed an analytical solution to detect leakage through pressure-monitoring wells screened in the geologic formations overlying the injection point. They showed that their model is capable of locating and quantifying the leakage of CO_2 and found a positive correlation between the accuracy of the estimation and the number of available monitoring wells. Also, Nogues et al. [12] developed an analytical solution to estimate the CO_2 and brine leakage from pressure variations observed at monitoring wells and investigated optimal location of the monitoring wells to improve leakage detection. Park et al. [13] proposed a methodology to detect CO_2 leakage by measuring pressure changes at monitoring wells with a constrained distribution. Sun and Nicot [14] presented an inversion method based on a global optimization algorithm to identify CO_2 leakage through leaky wells from pressure anomalies observed in the layers overlying the injected aquifer.

Analytical solutions and optimization algorithms constitute appealing tools for leakage detection. However, typical analytical solutions are based on highly idealistic assumptions and do not account for system heterogeneities. Improved accuracy of estimation can be achieved by using numerical models. Optimization algorithms may present a high computational cost. A reduction of the computation cost may be achieved by resorting to Monte Carlo inverse methods and ensemble-based Kalman filter (KF) [15] data assimilation methods. With respect to these two methods, Hendricks Franssen and Kinzelbach [16] performed a comparison between an ensemble-based KF and a Monte Carlo sequential self-calibration inverse method to characterize a heterogeneous transmissivity field. They found that the ensemble-based KF method requires a less central processor unit (CPU) effort than the Monte Carlo based method.

For CO_2 leakage detection problems, an attractive feature of KF methods lies in their intrinsic ability to assimilate data into uncertain model results as they are collected, that is, in real time. Data assimilation methods have been used in various earth science disciplines to update model states [17–19] and system parameters [17,20] based on field observations. The classical KF [15] provides an optimal solution in the case of linear Gaussian systems and unbiased measurements. Expanding the applicability of KF to nonlinear problems can be achieved by using an ensemble of realizations to approximate the prior uncertainty in states and parameters [21]. According to Evensen [22], ensemble-based KF methods can be subdivided into three main categories depending on the scheme adopted to assimilate measurements: (1) ensemble Kalman smoother (EnKS) algorithms, (2) ensemble Kalman filter (EnKF) algorithms, and (3) ensemble smoother (ES) algorithms. Some examples of successful applications of the EnKS can be found in the literature [23–25]. Examples of EnKF applications are reported by Chen and Zhang [17], Hendricks Franssen and Kinzelbach [26], and Li et al. [27]. Skjervheim and Evensen [28] effectively applied the ES to solve the history-matching problem in a petroleum reservoir and compared it with the EnKF. Bailey and Bau [29] used the ES to obtain the hydraulic conductivity through assimilation of water table height and stream flow rate data. Herrera and Simuta-Champo [30] applied the ES to optimize the location of sampling wells and the depth of the measurements in an aquifer.

To provide an optimal solution, these ensemble-based KF methods require: (a) unbiased and uncorrelated observation errors, (b) parameters and state variables to fit to multi-Gaussian distributions, and (c) a linear relationship between predicted data and model data. Since in practical applications at least one of these assumptions is often not satisfied, there is a need to devise approaches to circumvent these limitations. For example, to avoid the problem of non-Gaussianity, Gu and Oliver [31] successfully applied the normal score transform (NST) [32] to saturation data in a one-dimensional multiphase reservoir. Other more recent studies have addressed issues of non-Gaussianity of state variables or parameters [e.g. 20,33,34–37].

In this work, we propose an inverse modeling method based on the assimilation of fluid pressure data collected in strata above the target carbon storage formation. The inverse modeling framework relies on the combination of a subsurface multiphase flow model with ensemble-based data assimilation algorithms. The objective of this study is to investigate and compare the capabilities of the ES and a modified "restart" version of the EnKF (REnKF) to identify the presence of brine and/or CO_2 leakage pathways through the caprock formation during GCS operations. To the best of our knowledge, this is the first time that the ES and the REnKF are applied to detect caprock discontinuities by collection of pressure data from the aquifer overlying the storage formation.

Issues related to the non-Gaussianity of caprock permeability field are also examined. For the purpose of this study, we assume that changes in pressure in the upper aquifer are either observed at monitoring wells or provided by 4D seismic time-lapse surveys. To pose the CO_2 detection problem as an inverse estimation of caprock permeability from known pressure measurements, we assume that leakage areas can be represented as regions with high permeability, resulting in a non-Gaussian bimodal distribution of the caprock permeability. To overcome issues of non-Gaussianity of the caprock permeability spatial distribution a NST procedure is developed and implemented. The multiphase flow model used in this work is ECLIPSE [38], a reservoir simulator widely used in the petroleum industry. For the practical purposes of our numerical investigations, idealized assumptions of multiphase flow are made for the model setup.

This paper is organized as follows. Section 2 presents first the multiphase flow governing equations, followed by the ES and REnKF algorithms. Section 3 presents and compares the results of the application of these two methods for identifying potential leakage areas of the caprock during GCS operations and provides a thorough discussion on model assumptions. Finally, Section 4 summarizes the major findings of the present work.

2. Methodology

In this section, a basic description of the multiphase flow model ECLIPSE [38] used in the numerical experiments is given. Next the ES and the REnKF algorithms are described, followed by the definition of parameters used to assess their performance.

2.1. Multiphase flow model

Movement of CO_2 injected in brine aquifers is simulated using the reservoir model ECLIPSE [38]. In particular, its compositional version E300 is adopted to perform two-phase "compositional" simulations of gas–brine systems, based on the mass balance equations of N_c generic fluid components. E300 relies on the formulation of Trangenstein and Bell [39], which considers the total molar density (moles per pore volume) of each component $\hat{\rho}_j$ $(j = 1, 2, \ldots, N_c)$ as partitioned among different phases. Assuming the presence of only two fluid phases, a CO_2-rich gas phase, denoted as g, and H_2O-rich liquid phase, denoted as w, $\hat{\rho}_j$ must equal the sum of the gas molar density