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Inversion of pressure anomaly data for detecting leakage at geologic carbon sequestration sites

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ABSTRACT

Leakage from abandoned wells and geologic faults represents one of the greatest risks to the integrity of geologic CO_2 sequestration sites. The ability to detect leakage in a timely manner is, therefore, crucial for mitigating the potential adverse impacts of leakage to the public and environment. We present an inversion approach for recovering both leakage locations and rates by using observed pressure anomaly data. The approach is based on formulation of a linear system of equations using the unit-step response method, which is applicable to both analytical and numerical models. Because the resulting system is often ill conditioned, we investigate the efficacy of regularization methods for stabilizing the solutions. Further, when prior information is insufficient to restrict the number of search locations, a global optimization algorithm is used to solve the challenging problem of joint location and leakage history inversion. The performance of several linear inversion solvers is compared while considering effects such as measurement error and spatial heterogeneity. The results are promising and suggest that our pressure-anomaly-based leakage detection algorithm can be used to identify leaky wells in practice. It can be deployed as an integrated component of CO_2 risk management frameworks.

1. Introduction

Sequestration of carbon dioxide (CO_2) in deep geologic formations is being investigated globally as a promising technology for reducing greenhouse gas emission. Common geologic sequestration sites can be grouped into three main categories: depleted hydrocarbon reservoirs, brine-bearing "saline" formations, and unmineable coal seams [1]. A major risk of unplanned CO_2 migration from these geologic sequestration formations is related to the presence of pre-existing geologic features (e.g., faults and fractures) and wells that penetrate the primary confining interval. Leakage through improperly plugged and abandoned wells is considered the most probable CO_2 migration pathway [2,3], which is especially of concern for depleted reservoirs or enhanced oil recovery fields that have been intensively explored and exploited in the past for hydrocarbon production.

Failure to prevent or mitigate CO_2 leakage may cause (i) pollution of underground sources of drinking water (USDW), (ii) adverse impacts on public health and safety and nearby ecosystems, (iii) seepage of greenhouse gas to the atmosphere, and (iv) damage to adjacent natural resources. Therefore, a key performance measure of all CO_2 sequestration projects is to demonstrate that CO_2 can be safely stored over extended periods of time in a manner that is compliant with the best engineering practices and environmental regulation and that ensures protection of public health and safety. Ultimately the success of geologic CO_2 sequestration projects critically depends on emplacement of integrated systems for site characterization, modeling, monitoring, risk assessment, and public education. Many risk management paradigms and frameworks have been proposed in recent years. Although not mutually exclusive, existing methods can be classified broadly into (i) scenario-based approaches, in which critical system features, events, and processes (FEP) are identified, and probabilities and consequences of various scenarios are estimated through expert elicitation or stochastic simulation [4–7]; and (ii) life-cycle-management-based approaches, which rely on monitoring, verification, and accounting (MVA) technologies to assess the migration and fate of CO_2 plumes during different stages of operation and to ensure that the plume is contained in storage formations [3,8,9].

Not surprisingly, an essential component of all these risk assessment and management systems is the assessment of potential leakage through pre-existing wells, a task that recurs in all project stages. During the pre-operational stage, well integrity analysis is conducted to identify failure mechanisms associated with each component of a well; well tests are then conducted, followed by corrective actions if necessary [10–12]. Because of the different well completion and abandonment techniques used and the lack of complete records in many cases, a great deal of uncertainty remains. Moreover, inactive wells represent an increasing safety

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and environmental risk over the project life, even if they pass the initial integrity test. Therefore, during preliminary risk assessment, the likelihood of the CO_2 plume or pressure build-up region reaching abandoned wells is assessed [5,6,13,14] and the most risk-significant processes/parameters are identified. For given well locations, both semi-analytical solutions [15–17] and numerical models [18–21] have been developed to help assess the pressure buildup, leakage rates, and potential damages resulting from CO_2 injection. During the injection and post-closure stages, a closely-related but more challenging problem is leakage detection. More specifically, how can we analyze system anomaly data collected by a monitoring network to identify leakage locations and rates in a timely manner? This question can be considered the inverse problem of CO_2 leakage forward modeling and scenario-driven risk prediction.

Previously, Lewicki et al. [22] presented a detection strategy that integrates near-surface measurements of CO_2 fluxes/concentrations with an algorithm that enhances temporally- and spatially-correlated leakage signals. Fessenden et al. [23] demonstrated the effectiveness of several MVA technologies for detecting CO_2 leakage from a controlled release experiment. Lemieux [24] and Seto and McRae [25] gave detailed reviews of various existing monitoring techniques that can detect leakage signals, including, for example, geochemical, geophysical, and remote sensing techniques. A consensus of these studies is the need to deploy multiple monitoring techniques, and the need to integrate observations, process models, and uncertainty quantification. In addition, cost-benefit analysis can be very useful for exploring trade-offs between cost, safety, and risk.

The focus of this study is on the inversion of above-zone pressure anomaly data for detecting leakage history (i.e., leakage rate as a function of time) and location(s). We chose pressure anomaly data because (i) pressure signals travel fast ($\propto \sqrt{t}$) and usually give the first indication of leakage; (ii) pressure monitoring data are effectively continuous and can provide information for both history matching and leakage detection; (iii) the costs associated with pressure data acquisition are relatively low; and (iv) detection based on pressure anomaly has a low requirement for proximity to source locations, which is in contrast to many other near-surface monitoring technologies. Although our methodology is similar to the concept of source identification, which has long been studied in contaminant transport and water distribution system management [26–32], its application to geologic CO_2 sequestration is novel. In addition, important differences exist between pressure inversion and contaminant source inversion in terms of source characteristics, physical processes involved, and location and frequency of monitoring.

The rest of this paper is organized as follows. Section 2 describes the mathematical formulation of our pressure anomaly inversion algorithm for leakage history and location identification, Section 3 demonstrates the algorithm through different numerical experiments, and finally, the main findings are summarized in Section 4.

2. Methodology

2.1. Formulation of the pressure inversion problem

Let us consider an aquifer in which pressure is being monitored. This can be either a deep or shallow USDW above the injection zone. To be consistent with hydrogeology terminology, we shall use *head* instead of *pressure* in the following discussion. We will also use *leaky well* and *source* interchangeably.

Our starting point is the governing equation for saturated groundwater flow:

$$\begin{aligned} S_s(\mathbf{x})\frac{\partial h(\mathbf{x},t)}{\partial t} + \nabla\cdot\mathbf{q}(\mathbf{x},t) = Q_w(\mathbf{x},t) \\ \mathbf{q}(\mathbf{x},t) = -K_s(\mathbf{x})\nabla h(\mathbf{x},t), \end{aligned} \tag{1}$$

which is subject to initial and boundary conditions

$$h(\mathbf{x},0) = H_0(\mathbf{x}), \quad \mathbf{x}\in\Omega, \tag{2}$$

$$h(\mathbf{x},t) = H_b(\mathbf{x},t), \quad \mathbf{x}\in\Gamma_D, \tag{3}$$

$$\mathbf{q}(\mathbf{x},t)\cdot\mathbf{n}(\mathbf{x}) = Q_b(\mathbf{x},t), \quad \mathbf{x}\in\Gamma_N, \tag{4}$$

where h is hydraulic head; $\mathbf{q}$ is Darcy flux; S_s is specific storage; K_s is saturated hydraulic conductivity; Q_w is the sink/source term; H_0 is initial condition; Ω denotes the interior of the model domain; H_b and Q_b define the Dirichlet and Neumann boundary conditions on boundary segments Γ_D and Γ_N, respectively; and $\mathbf{n}(\mathbf{x})$ is an outward unit vector normal to the boundary. The solution to the PDE system prescribed by Eqs. (1)–(4) has long been studied in groundwater literature. The linearity of the system allows expressing the solution in terms of convolution integrals [33]

$$\begin{aligned} h(\mathbf{x},t) = &\int_0^t\int_\Omega Q_w(\mathbf{y},\tau)G(\mathbf{y},\mathbf{x},t-\tau)d\mathbf{y}d\tau \\ &-\int_0^t\int_{\Gamma_D} K_s(\mathbf{y})H_b(\mathbf{y},\tau)\nabla_{\mathbf{y}}G(\mathbf{y},\mathbf{x},t-\tau)\cdot\mathbf{n}(\mathbf{y})d\mathbf{y}d\tau \\ &+\int_0^t\int_{\Gamma_N} Q_b(\mathbf{y},\tau)G(\mathbf{y},\mathbf{x},t-\tau)d\mathbf{y}d\tau \\ &+\int_\Omega S_s(\mathbf{y})H_0(\mathbf{y})G(\mathbf{y},\mathbf{x},t)d\mathbf{y} \end{aligned} \tag{5}$$

In Eq. (5), $G(\mathbf{y},\mathbf{x},\tau)$ is Green's function (also known as the kernel function, unit-pulse response function, or fundamental solution) obtained by solving the following PDE

$$S_s\frac{\partial G(\mathbf{y},\mathbf{x},\tau)}{\partial\tau} + \nabla_{\mathbf{y}}\cdot(K_s(\mathbf{y})\nabla_{\mathbf{y}}G(\mathbf{y},\mathbf{x},\tau)) = \delta(\mathbf{x}-\mathbf{y})\delta(t-\tau) \tag{6}$$

which is subject to homogeneous initial and boundary conditions and a unit impulse $\delta(\mathbf{x}-\mathbf{y})\delta(t-\tau)$ centered at location $\mathbf{y}$ and time τ, where $\delta(\cdot)$ is the Dirac-Delta function. Therefore, $G(\mathbf{y},\mathbf{x},\tau)$ essentially encapsulates all physical characteristics of the system. Analytical solutions of Eq. (5) exist only for simplistic problem settings. For example, a semi-analytical solution derived by Nordbotten et al. [15] assumes constant initial head distribution and infinite lateral boundaries. In general, numerical methods must be used to obtain unit response functions.

Our main interest in this work is the inverse problem, namely, reconstruction of the leakage history (i.e., the sink/source term, Q_w) based on head observations collected at different times and locations. Leakage history is a continuous function of time and, therefore, needs to be parameterized to reduce the number of unknowns. If there are M potentially leaky wells and the total study period is $[0, T]$, the simplest parameterization method is to divide the study period $[0, T]$ into N intervals, $\{\Delta t_j\}_{j=1}^N$, and assume constant source strength in each interval (i.e., a stair function). For example, the leakage rate for the ith leaky well becomes a vector, $\mathbf{s}_i = [s_{i1}, \ldots, s_{iN}]$. Using such parameterization, we can represent the sink/source term appearing on the right-hand-side of Eq. (1) as

$$Q_w(\mathbf{x},t) = \sum_{i=1}^M\sum_{j=1}^N s_{ij}\delta(\mathbf{x}-\mathbf{x}_i)\delta(t-T_j) \tag{7}$$

where δ is the Kronecker delta function, and T_j denotes the jth time interval. Therefore, the total number of unknowns becomes $P = MN$. Substituting Eq. (7) into Eq. (1), we can obtain a discrete version of the convolutional integral (5) by superposing P unit-step response functions, each obtained by replacing the right-hand-side of Eq.