International Journal of Greenhouse Gas Control 52 (2016) 32–43

Contents lists available at ScienceDirect

International Journal of Greenhouse Gas Control

journal homepage: www.elsevier.com/locate/ijggc

Use of above-zone pressure data to locate and quantify leaks during carbon storage operations

David A. Cameron*, Louis J. Durlofsky, Sally M. Benson

Department of Energy Resources Engineering, Stanford University, Stanford, CA 94305, USA

ARTICLE INFO

Article history:
Received 10 July 2015
Received in revised form 9 June 2016
Accepted 14 June 2016

Keywords:
Carbon storage
Sequestration
Optimization
Data assimilation
History-matching
Leakage

ABSTRACT

We determine the potential accuracy in estimating the size and location of leaks in the caprock by history-matching above-zone pressure monitoring data to leakage models. The number of monitoring wells and the total monitoring time is varied in order to determine minimum pressure-monitoring requirements for effective leak characterization. The history-matching procedure uses particle swarm optimization to minimize the error between leakage-model solutions and synthetic observation data by adjusting model parameters governing the size and location of the leak, as well as the heterogeneous permeability field throughout the model. The method applies to storage projects with uncertain heterogeneous geology that may be described by a variogram model. Results from several examples indicate that as little as 6–12 months of above-zone pressure monitoring data, collected from at least 3 or 4 wells, may be sufficient to locate and estimate the size of a leak to inform mitigation and remediation strategies. No significant benefit is seen when using multilevel monitoring wells versus single-level monitoring wells. We also find that adding white noise to the synthetic observation data, with magnitude consistent with current pressure monitoring techniques, generally reduces error in solutions, likely due to a regularization effect. Taken in total, the results and procedures introduced in this study should be of use in designing monitoring strategies in large-scale carbon storage projects.

1. Introduction

A major concern associated with carbon capture and storage (CCS) in saline aquifers is the potential for leakage. While thorough pre-injection screening procedures have been developed to avoid caprock-leakage; it is important that, in the event there is a leak, we are able to quickly detect, locate and quantify it so that risk-assessment and remediation efforts can be initiated. In this work, we investigate the efficacy of history-matching above-zone pressure monitoring data in order to locate and quantify such leaks.

Much research has been dedicated to understanding the physical processes of leakage. Information and examples of flow through faults in CCS related operations are provided in Lewicki et al. (2007). The probability of a plume encountering a fault was investigated by Jordan et al. (2011) using a fault density distribution model. For their case study in the San Joaquin Basin, they found that a previously planned injection site had a 3% chance of encountering a large enough fault to cause significant leakage. Leakage through abandoned wells has also been studied by numerous authors, for example, Nordbotten et al. (2005) developed a semi-analytical model for flow through leaky wellbores. The likelihood of a plume encountering an abandoned well was investigated by Gasda et al. (2004), based on the distribution of wells in a well-studied area of the Alberta Basin in Canada.

There are several monitoring options for leakage detection in CCS operations, as detailed in Plasynski et al. (2011). Methods relying on surface detection of CO_2 have been proposed by, e.g., Lewicki et al. (2007) and Fessenden et al. (2010). While these methods may be effective at determining when leakage has occurred, leakage should ideally be identified before it has reached the surface. Early detection monitoring techniques involving well data, seismic data, tracers, and satellite interferometry have been applied at both the In Salah and Sleipner storage projects. At the In Salah site, a combination of surface uplift data and measured CO_2 breakthrough at a monitoring well confirmed that leakage had occurred. This leakage was largely attributed to one of the three CO_2 injectors (Ringrose et al., 2009), which was subsequently shut in.

Because pressure responses in the subsurface propagate quickly, pressure data from monitoring wells may be used to detect, and possibly locate, leaks before CO_2 has even reached them. Pressure

* Corresponding author.
E-mail address: davecame@gmail.com (D.A. Cameron).

http://dx.doi.org/10.1016/j.ijggc.2016.06.014
1750-5836/

transient data has been used to monitor and infer the migration of CO_2 within the storage reservoir using multilevel pressure sampling at the Illinois Basin Decatur Project (Strandli et al., 2014). Using an approach developed by Strandli and Benson (2013), it was demonstrated that CO_2 was trapped beneath a thin sealing layer far below the base of the regional seal created by the Eau Claire shale formation. The application of these data showed that multilevel pressure sampling, even within the storage reservoir itself, provides valuable information, which could potentially aid in detecting CO_2 migration and predicting leakage.

The detectability of leaks using above-zone pressure-transient data was analyzed by Chabora and Benson (2009). They found that pressure transient data can indicate CO_2 breakthrough in some cases, though their tests were performed on simplified aquifer models with known geology. The work of Sun and Nicot (2012) confirmed that pressure anomalies indicating leakage are detectable even when measurement error and spatial heterogeneity are considered. Sun et al. (2013b) used a probabilistic collocation method to determine when pressure data might be used to detect leakage. Their method considers the signal-to-noise ratio of pressure anomaly data and provides an effective means for detecting when a leak exists. A methodology to determine optimal monitoring well locations to minimize both the chance, and consequences, of not detecting a leak was presented in Sun et al. (2013a). They assumed a minimum pressure signal for leak detection and did not consider whether monitoring networks could predict the locations or leakage volumes of leaks via data assimilation.

A method to determine both the location and transmissibility of a leak from above-zone pressure monitoring data, collected over as little as a 50 day period, was initially proposed by Javandel et al. (1988). Their method assumes that the aquifer pressure can be characterized using the Theis equation (Theis, 1935), which is an analytical approximation of the pressure response from single-phase injection into an infinitely large, horizontal, homogeneous aquifer. An analysis of the stability and uniqueness of the inversion, using the Theis equation for pressure propagation, was carried out by Zeidouni and Pooladi-Darvish (2012a). The extension of that work (Zeidouni and Pooladi-Darvish, 2012b) used the inversion method to evaluate aspects that might improve the efficacy of monitoring. It was found that both pulsing injection and including additional monitoring wells reduces error in predicting the location of a leak. While the Theis equation has since been extended by Zeidouni (2014) to provide vertical pressure data, its application is restricted to homogeneous, horizontal aquifers with a single point of leakage. In more complicated (realistic) scenarios, simulation is required to forward-model the propagation of pressure. As a result, the data assimilation process is more difficult.

Data assimilation (also known as inversion, history-matching or model updating) refers to the determination of one or more geological models that match observed dynamic data to within some tolerance. Several studies have focused on data assimilation to improve the conceptual model of the storage formation and, sometimes, the overlying (above-zone) aquifer. Some of these used data collected from actual storage operations, while others used synthetic data to test methodologies. Many of the history-matching studies to date (e.g., Doughty et al., 2008; Ennis-King et al., 2011) considered simplified facies and 'layer-cake' models and included only a small number of geological parameters, which were generally matched by hand. In the case of Doughty et al. (2008), cross-well seismic and vertical seismic profile (VSP) data were collected (see also Daley et al., 2008) from the Frio formation near Houston, Texas. The forward model for history-matching involved both flow and seismic modeling, with seismic signals providing the observation data to be matched. In the case of Ennis-King et al. (2011), bottomhole pressure data from the depleted Naylor gas field in Southeastern Australia were used for history-matching.

In order to facilitate efficient data assimilation in an uncertain heterogeneous geologic setting with thousands of geologic variables, parameterization procedures can be applied to reduce the number of variables. One such technique, the Karhunen–Loève (K–L) expansion (Loeve, 1977), has been used in oil field applications (e.g., Oliver, 1996; Reynolds et al., 1996; Sarma et al., 2006), and more recently in the context of carbon storage (e.g., Cameron and Durlofsky, 2014). K–L expansion, which is analogous to principal component analysis (PCA), is most applicable in geologic settings with relatively smooth property variations, where the model parameters (e.g., porosity and permeability) are correlated according to their relative locations. Such a setting corresponds to a Gaussian or 'two-point' geostatistical model. A major benefit of the K–L expansion is that random samples of the K–L variables produce geologic realizations that honor the two-point geostatistics as defined by prior models (this is also the case for history-matched models generated via the K–L variables). By prior models, we mean realizations that honor the specified spatial statistics and any available 'hard' data, but not dynamic flow data (which is why history-matching is necessary). Extensions of the K–L parameterization include the kernel principal component analysis (KPCA, see Sarma et al., 2008) and optimization-based principal component analysis (O-PCA, see Vo and Durlofsky, 2014) methods. These treatments enable the representation of geologically-realistic systems characterized by multipoint (rather than two-point) spatial statistics. Examples of such systems include channelized or deltaic-fan geologies.

The use of data assimilation to locate a leak from simulated above-zone pressure data was addressed, in some aspects, by Jung et al. (2015). There, the accuracy in predicting the leak location was tested against several uncertain model parameters, including the size and permeability of the leak, the thickness and permeability of the caprock, and other storage formation and above-zone properties. They did not, however, test the effect of using more than two monitoring wells, nor did they consider different leak locations or heterogeneous geologies. A major conclusion from Jung et al. (2015) is that leak location estimates based on concurrent above-zone and storage formation pressure data are more accurate than estimates using only above-zone data, which are in turn much more accurate than estimates using only the storage-formation data. This claim is supported by Cameron (2013), though that work suggested that the modest benefit from including storage formation data may not be worth the capital expenditure (and risk of damaging the caprock) needed to acquire it.

In Cameron (2013), the methods of K–L expansion and particle swarm optimization (Kennedy and Eberhart, 1995) were shown to be effective in performing carbon sequestration data assimilation in problems with uncertain heterogeneous geology. It is the goal of this work is to expand upon the work of Cameron (2013), Sun et al. (2013a) and Jung et al. (2015) to provide an assessment for the predictability of leak locations and leakage volumes, given different numbers of above-zone monitoring wells, over different monitoring time-periods, in an uncertain heterogeneous environment.

This paper proceeds as follows. In the methodology section, we first describe the leaky aquifer model used in this study, then provide relevant theory on data assimilation and the K–L expansion, and finally present our formal data assimilation problem statement. In the results and discussion section, we assess the impact of (1) temporal data quantity, (2) the number and location of monitoring wells, (3) the use of multilevel versus single-level monitoring wells, and (4) the use of higher-resolution leakage models. We conclude with a summary of our major findings and suggestions for future work.