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3 **Saline Sequestration Sites Using Pressure**
4 **Measurements**

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A Bayesian Approach to CO₂ Leakage Detection at Saline Sequestration Sites Using Pressure Measurements

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Abstract

Diffusive leakage of CO₂ through the sealing caprock is likely to occur at saline sequestration sites if the permeability of the caprock is too high. Pressure monitoring is a widely used technique for CO₂ leakage detection. This study aims to characterize the CO₂ leakage level in an idealized CO₂ storage site through an assessment of the integrity and permeability of the caprock inferred from pressure measurements in the injection zone. Monte Carlo uncertainty analysis is conducted, allowing the detection power of pressure measurements to be estimated. Based on Bayesian classification theory, the probability of each caprock permeability class given pressure measurements with measurement error can be inferred. The influence of time and location of measurements, the relative magnitude of the measurement error, the CO₂ injection rate, and the assumed uncertainty in reservoir properties on the inferred caprock permeability class and the detection power of the pressure monitoring is also evaluated. Pressure monitoring alone is not sufficient to detect a permeable caprock for the system considered in this study, unless the caprock permeability is very high. A significant improvement in the statistical detection power is evident in the case where the uncertainty in reservoir properties is reduced through further site characterization. Complementary monitoring techniques will likely be needed to improve the power of pressure-based CO₂ leakage detection to acceptable levels.

Keywords

Carbon sequestration; Leak detection; Pressure monitoring; Bayesian classification; Caprock

1. Introduction

Geological carbon sequestration is considered a promising strategy for mitigating potential climate change associated with increasing CO₂ concentration in the atmosphere (Hepple and Benson, 2005; IPCC, 2005). To have a significant effect on the atmospheric concentration of CO₂, large amounts of CO₂ need to be captured from electric power plants and industrial sources and injected into deep underground formations, such as saline aquifers, depleted oil and gas reservoirs and unmineable coal seams (Holloway, 2005; Gale, 2004). Deep saline aquifers are estimated to have the highest CO₂ storage potential among all the geological storage options (USDOE, 2010).

To demonstrate that the implementation of carbon sequestration is safe and effective as a greenhouse gas control technology, monitoring CO₂ stored in deep saline aquifers is crucial (Benson and Myer 2002). Multiple monitoring techniques can be applied at different depths, including atmospheric monitoring, near-surface monitoring and deep subsurface monitoring. (Benson and Myer, 2002; USDOE, 2009). Studies to characterize the performance of near-surface monitoring techniques, including near-surface soil CO₂ flux measurements and tracer measurements, have been undertaken (Yang et al., 2011a; Yang et al., 2011b). A Bayesian belief network methodology, integrating multiple monitoring techniques for CO₂ leak detection, has also been demonstrated by Yang et al. using near-surface monitoring techniques (Yang et al., 2012). A review of alternative statistical methods and perspectives for leak detection monitoring and inference is provided by Jenkins (2013). The costs of deploying different monitoring techniques were evaluated by Benson et al. (2004).

One broadly recommended and cost-effective monitoring technique is pressure monitoring in the injection and above zone reservoirs (Meckel et al., 2008). Measurements of injection pressures at the wellhead and in the formation are common in oil field practice (Benson and Myer, 2002). An above-zone monitoring technique that also measures pressure changes in a permeable zone overlying the injection zone has been deployed in the Cranfield CO₂ Storage Project (Meckel et al., 2008). The continuous pressure changes in the injection zone and those in the above zone during CO₂ loading can be measured simultaneously once downhole pressure gauges are equipped in the monitoring wells. Unanticipated pressure changes in both zones can also be used as indicators of a fluid migration out of the injection zone (Meckel et al., 2008; Chabora and Benson, 2009). The range of anticipated conditions under leak vs. no-leak scenarios can be characterized using reservoir flow and pressure models.

Semi-analytical solutions have been derived to describe the space-time evolution of a CO₂ plume during injection and CO₂ leakage through an abandoned well (Nordbotten et al. 2005a; Nordbotten et al. 2005b). This semi-analytical model was further applied to a specific field site in Alberta, Canada to perform a risk analysis of CO₂ and brine leakage along old wells (Celia et al., 2011). The sensitivity and uncertainty analysis of pressure measurements has been studied by several authors (Birkholzer et al., 2009; Chabora and Benson, 2009; Sun et al., 2013a).

In the paper by Sun et al., a particular uncertainty-quantification technique especially well-suited for computationally complex models, the probabilistic collocation method, is used to assess leakage detectability based on the signal to noise ratio of pressure perturbations predicted to occur from leakage. In a related paper an optimization method is formulated for designing a pressure-based monitoring system at carbon sequestration sites (Sun et al., 2013b). Azzolina et al. (2013) also propose a probabilistic framework for leak detection based on pressure monitoring. They utilize a multilayer reservoir pressure model to predict system response to CO₂ injection and evaluate its response using an approximate first-order uncertainty analysis method.

Our analysis is similar in concept, but uses a more aggregate analytical model for the subsurface and more advanced methods for uncertainty analysis based on Monte Carlo simulation and Bayesian inference regarding caprock states and potential associated leakage rates.

Injected CO₂ could leak slowly and diffusively through a sealing caprock, or leak relatively quickly through high permeability conduits, such as faults and abandoned wells. Depending on the kind of storage formation, one leakage pathway might be more likely than the other. For example, as the sealing caprock in a depleted oil and gas reservoir is usually well defined and there might be abandoned wells present from former reservoir operations, the most likely pathway for leakage is through the boreholes of the wells. For saline aquifers, the sealing caprock is less well defined or lacks a structural trap at some locations. The most likely pathway would then be through the caprock if its permeability is not low enough (Benson and Myer, 2002). The high pressure buildups after CO₂ injection into the storage formation could potentially hydraulically fracture the caprock (Chiaramonte et al., 2007). This mechanism might trigger higher effective permeability and a greater resulting chance for CO₂ leakage through the caprock (Liu et al., 2012).

This study focuses on diffusive CO₂ leakage through the sealing caprock and the resulting pressure changes in the injection zone. The objective of this study is to characterize the CO₂ leakage level through an assessment of the integrity and permeability of the caprock inferred from pressure measurements and to evaluate the detection power of the pressure monitoring technique. The uncertainty of the pressure in the injection zone is estimated from Monte Carlo simulation of pressure buildups using a simplified geological reservoir model. Pressure measurements are assumed to be made with error, considering low, medium and high coefficients of variation for each measurement, conditioned on the modeled value. Based on Bayesian classification theory, the probability of each caprock permeability class given the observations of pressure in the injection zone can then be inferred. The power of pressure monitoring to detect a leaky, high-permeability caprock is also evaluated from the simulation results. Further, we evaluate the influence of time and location of measurements, the magnitude of the measurement error, the CO₂ injection rate, and the uncertainty in reservoir properties on the inferred caprock permeability class and the detection power of the pressure monitoring. The uncertain reservoir properties considered here include the thickness, permeability and porosity of the injection zone and the above zone.

2. Model Setup and Uncertainty Analysis

2.1. A simplified geological reservoir model

The CO₂ storage site is modeled as a confined system with two aquifers separated by a sealing caprock of thickness 120 m (Figure 1). The lower aquifer is the injection zone and the upper

aquifer is the above zone. The injection zone is at a depth of 2000 m below the ground surface and the temperature is assumed to be 65 °C. The initial pressures in the injection zone and the above zone are stable at 2×10^7 Pa and 1.97×10^7 Pa, respectively. Each layer (the injection zone, the sealing caprock and the above zone) is assumed to be homogeneous, isotropic and with infinite radial extent. An injection well completely penetrates the above zone and the caprock, and is screened at the top of the injection zone. CO₂ is continuously injected into the injection zone from the injection well at a fixed rate. A base-case observation well is located 500 m away from the injection well, with monitoring wells at 100 m and 1000 m also considered in a sensitivity analysis. Pressure buildups in the injection zone after continuous injection of CO₂ over 1, 2, 5, 10 and 20 years are calculated using the analytical solutions derived by Neuman and Witherspoon (1969).

Figure 1 Schematic diagram of the simplified geological reservoir model, adapted from Neuman and Witherspoon (1969).

The Neuman-Witherspoon analytical solution is a single-phase solution, originally developed for the problem of transient flow to a well in a confined two-aquifer system. The equations have been previously used to calculate pressure buildups after CO₂ injection at carbon sequestration sites by Chabora and Benson (2009). In the Neuman-Witherspoon solution, the pressure change is expressed as an infinite integral of a highly oscillating function. This integral is solved numerically using the adaptive Simpson quadrature in MATLAB (Gander and Gautschi, 2000; Chabora and Benson, 2009). The equations of the Neuman-Witherspoon analytical solutions and the MATLAB codes are listed in Appendix A. Solutions are obtained with relatively short computation time, allowing Monte Carlo uncertainty analysis (with 20 scenarios and a sample size of $n=1000$ replications for each scenario) to be conducted for the predicted pressure buildups.

2.2. Uncertainty in pressure evolution

The uncertainty in pressure evolution following initiation of the CO₂ injection is quantified using the Neuman-Witherspoon solution implemented with Monte Carlo sampling of uncertain model inputs and parameters. The presumptive conditions of a carbon sequestration site and CO₂ injection rate used in the Monte Carlo uncertainty analysis are summarized in Table 1. These parameters are obtained from geological properties at the Cranfield CO₂ storage site (Meckel et al., 2008) and the reservoir conditions used by Chabora and Benson (2009), and are assumed to be fixed. The assumed uncertain inputs include the thickness, permeability and porosity of the injection zone and those in the above zone. The uncertain inputs are assumed to be independent variables with a specified distribution type. The geological properties in the above zone are assumed to follow the same distribution as those in the injection zone. Based on the permeability and porosity database developed by the National Petroleum Council (NPC, 1984), the distributions of uncertain inputs shown in Table 2 were selected to conduct the Monte Carlo uncertainty analysis. Scatter plots of permeability vs. porosity based on the NPC database can be found in Appendix A.3.

One assumption made in the Neuman-Witherspoon analytical solution is that the flow is vertical in the caprock and horizontal in the aquifers. As pointed out by Neuman and Witherspoon (1969), the permeability of the aquifers needs to be two or more orders-of-magnitude greater than that of the caprock in order to reduce the errors introduced by this assumption. Therefore, the assumed lognormal distribution of permeability in reservoirs is truncated to guarantee that the reservoir permeabilities are at least four orders of magnitude greater than that of the caprock. As this study focuses on the diffusive leakage of CO₂ through the sealing caprock, the caprock permeability class, defined by intervals of sealing caprock permeability values, is assumed to serve as a surrogate for the magnitude of CO₂ leakage (Table 3).

Table 1 Fixed reservoir and injection conditions assumed in Monte Carlo uncertainty analysis

Parameter	Symbol	Value
Depth (m)	H	2000
Temperature (°C)	T	65
Initial pressure in the injection zone (Pa)	pI_initial	2×10^7
Initial pressure in the above zone (Pa)	pM_initial	1.97×10^7
Porosity of the caprock	ϕ_c	0.05
Thickness of the caprock (m)	h_c	120
Total formation compressibility (Pa ⁻¹)	c_t	1×10^{-9}
Injection rate (MT-CO ₂ /yr)	Q	1
Radial distance from injection well (m)	R	500

175

176 Table 2 Distributions of uncertain input parameters assumed in Monte Carlo uncertainty analysis
 177 (based on values found in the National Petroleum Council database (NPC, 1984))

Parameter	Distribution Type	Mean (μ)	Standard deviation (σ)	Lower limit	Upper limit
Formation thickness, $h_{I/M}$ (m)	Normal	10	2		
Permeability, $k_{I/M}$ (mD)	Truncated Log10 normal	2^a	1^a	$10^4 k_c$	
Porosity, $\phi_{I/M}$	Truncated Normal	0.2^b	0.1^b	0.0005	0.6

178 a: The mean and standard deviation values are parameters of the lognormal distribution in base 10, that is,
 179 the mean and standard deviation of the base 10 logarithm of the variable before truncation.

180 b: The mean and standard deviation values are parameters of the normal distribution before truncation.

181

182 Table 3 Intervals of caprock permeability values representing different leakage levels

Caprock permeability, k_c (μ D)	CPC = Caprock Permeability Class	CO ₂ Leakage Magnitude	Assumed Prior Probability, $\pi(\text{CPC})^a$
0.1-1	1. Impermeable	Negligible	0.25
1-10	2. Moderate	Moderate	0.25
10-100	3. High	High	0.25
100-1000	4. Very High	Very High	0.25

183

184 Given the assumed distributions of uncertain inputs, Monte Carlo simulations were run for five
 185 caprock permeability values within each caprock permeability class, resulting in 20 caprock
 186 permeability scenarios in total. Each execution of the Monte Carlo model simulates (using the
 187 Neumann-Witherspoon analytical solution) 1000 different temporal profiles of pressure buildup
 188 in the injection zone at a location 500 m away from the injection well. Pressure buildups in the
 189 above zone can also be calculated using the Neuman-Witherspoon solution, but are not as
 190 responsive as those in the injection zone when the caprock permeability increases. The value of
 191 adding a second measurement (i.e., the above-zone pressure) is further diminished by the
 192 presence of measurement error. Therefore, this study focuses solely on pressure buildups in the
 193 injection zone. Pressure values are noted and evaluated at $t=1, 2, 5, 10$ and 20 years following

the initial injection. As indicated in Table 1, a continuous injection rate of 1 MT CO₂/yr is maintained over the 20-year simulation period. The simulated uncertainty in pressure buildups in the injection zone (i.e. pressure changes, Δp_I) after CO₂ injection at dividing points of caprock permeability classes is depicted in Figure 2, including the empirical 5th, 50th and 95th percentile values of the simulation results. As the caprock permeability increases, the uncertainty in the simulation results decreases markedly. Also, the pressure buildups in the injection zone (Δp_I) decrease as the caprock permeability increases. This is reasonable because, as the caprock permeability increases, more fluid from the injection zone is expected to migrate into the above zone through the caprock, resulting in a pressure decrease in the injection zone.

Figure 2 Simulated uncertainty in pressure buildups in the injection zone at 500 m from point of injection after injecting CO_2 with a) Caprock permeability $k_c = 0.1 \mu D$; b) Caprock permeability $k_c = 1 \mu D$; c) Caprock permeability $k_c = 10 \mu D$; and d) Caprock permeability $k_c = 100 \mu D$. Results shown are the median (solid line), 5th and 95th percentile values (dashed lines) of 1000 Monte Carlo simulations for the injection zone (ΔpI : pressure buildups in the injection zone, shown in red).

3. Bayesian Classification Methodology for CO_2 Leakage Detection

Bayesian theory provides a mathematical tool to combine an expert's belief regarding the probability of each caprock permeability class (CPC) with evidence obtained from field measurements. An expert's belief is represented by a prior distribution for the presence of each CPC at a site. In the Bayesian classification methodology, the prior distribution and the field measurements are combined using the likelihood function to derive the posterior distribution. If an uninformative prior distribution is assumed, the results will be objective, that is, totally dependent upon the field measurements. In this case, the posterior probability of a caprock permeability class is proportional to the likelihood function for the field pressure measurements, given each CPC.

The likelihood function for the field pressure measurements is composed of two components. The first is the uncertainty in the true value of the pressure in the injection zone (at a given location and time) that results from the uncertain reservoir properties; this uncertainty is captured by the 1000 discrete Monte Carlo simulation results. The second is the uncertainty associated

with measurement error when observing the pressure in the injection zone. This is captured by an assumed lognormal measurement error function that maps simulated true into simulated measured pressures. Combining these, the likelihood for each simulation is computed as the value of the measurement error probability density function evaluated at the observed value, assuming that the simulated value is true. The overall likelihood function for the full set of simulations (e.g., associated with a given caprock permeability class) is the total likelihood computed for each of the individual (e.g., 1000) simulations. This method is similar to that employed in Bayes Monte Carlo simulation (e.g., Dilks et al., 1992; Sohn et al., 2000; Pinder et al., 2004). The number of simulations allocated to each caprock permeability class is proportional to the prior probability for that class; in this case an equal number of simulations is allocated to each of the four CPC's.

3.1. Inferring caprock permeability class

Equal prior probability (= 0.25) is assigned to each of the four caprock permeability classes, as shown in Table 3. The pressure buildup in the injection zone (ΔpI) is chosen to be the measured variable for inference of caprock permeability class in this study. Generally, ΔpI would decrease as the caprock permeability increases. ΔpI ranges theoretically between zero and infinity. For the cases considered and simulated in our analysis, the value of ΔpI ranges from 10^{-4} MPa to 45 MPa. When measurement errors are also considered, observed values of ΔpI beyond these limits are possible.

To estimate the likelihood of observing ΔpI given each caprock permeability class, $f(\Delta pI|CPC_j)$, first, 1000 ΔpI values are computed for each of the caprock permeability classes, incorporating the fixed values in Table 1, the uncertain properties in Table 2 and a random sample of k_c from a uniform distribution within each caprock permeability class (for example $k_c \sim U(1, 10)$ for the moderate caprock permeability class). Second, to simulate the effects of measurement error, the injection zone pressure buildups ($\Delta pI_{measured}$) are assumed to be lognormally distributed about the true (model simulation) values:

$$\Delta pI_{measured} \sim \text{Lognormal}(a_I, b_I) \quad (1)$$

$$\text{with } a_I = \log(\Delta pI_{simulated})$$

$$b_I = [\log(c.v.^2 + 1)]^{1/2}$$

As indicated, the ΔpI results from each Monte Carlo simulation run specify the median values for the respective lognormal distributions of $\Delta pI_{measured}$ (specifying the parameters a_I , which

represent the logarithm of the median of the respective measurements), while the second parameter, b_I , corresponds to the standard deviation of the logarithm of $\Delta pI_{measured}$. For ease of interpretation, these second parameters are specified by the coefficients of variation of $\Delta pI_{measured}$: *c.v.*.

The lognormal distribution for $\Delta pI_{measured}$ is thus fully specified by the computed value of ΔpI_i for each simulation i and the assumed error (coefficient of variation) for each pressure measurement (determined by b_I , which is the same for all simulations). The pdf of the lognormal distribution serves as the likelihood function for the pressure observations given the simulation result:

Likelihood(simulation i) =

$$f(\Delta pI_{measured}|a_{Ii}, b_I) = \frac{1}{\Delta pI_{measured} * a_{Ii} * \sqrt{2\pi}} \exp \left\{ \frac{-(\ln(\Delta pI_{measured}) - a_{Ii})^2}{2b_I^2} \right\}$$

(2)

When a subset of the simulations is used to represent a particular case, (i.e., a particular CPC_j), then the case is represented by an “or” operation across the individual simulations in the subset, and the overall likelihood is given by the sum of the individual likelihoods. In the application that follows we utilize 1000 simulations for each case, so that:

$$\text{Likelihood}(\text{case } j) = \sum_{i=1}^{1000} f(\Delta pI_{measured}|a_{Ii}, b_I) \quad (3)$$

The prior distribution of caprock permeability class and the likelihood function are combined using Bayes rule (Equation 7) to calculate the posterior distribution of each caprock permeability class, $\pi(CPC_j|\Delta pI_{measured})$.

$$\pi(CPC_j|\Delta pI_{measured}) = \frac{f(\Delta pI_{measured}|CPC_j) * (CPC_j)}{\sum_{j=1}^4 f(\Delta pI_{measured}|CPC_j) * (CPC_j)}$$

(4)

3.2. Power Calculation

Leakage detection is assumed to occur whenever a permeable or a highly permeable caprock is inferred to be present from the results of the pressure measurements. This inference is made using a statistical test of hypothesis. The test may be set up to determine whether there is sufficient evidence in the data to very strongly support the argument that the caprock is

impermeable (the null hypothesis is that the caprock is permeable). Alternatively, a traditional approach used for regulatory compliance can be employed in which the caprock is assumed to be impermeable, unless the data provides very strong evidence that the caprock is permeable. While either approach can be implemented with the proposed methodology, here we demonstrate the latter (regulatory compliance) perspective in which the null and alternative hypotheses are given by:

H_0 : CPC = Class 1 (Impermeable)

H_1 : CPC = Class 2, 3, or 4 (Moderate, High, or Very High Permeability) (5)

We employ a Bayesian test of hypothesis in which the P-value for the test is computed as the probability of H_0 . This probability is calculated directly in Equation 4 as a function of $\Delta pI_{measured}$. If the P-value is low enough, this provides statistically significant evidence that the caprock is permeable, and H_0 is rejected. As such, we can identify a critical value of the measured pressure buildup in the injection zone, $\Delta pI_{measured_{crit}}$, beyond which the P-value falls below α , the significance level chosen for the test (e.g., $\alpha = 0.1, 0.05$, or 0.01). The chosen significance level also corresponds to the false positive (Type 1 error) rate for the test of hypothesis. Power is calculated as the probability that H_0 is rejected for simulations representing CPC Class 2, 3, or 4 (i.e. caprock permeability $k_c > 1 \mu D$); for CPC Class 1 (i.e. $k_c \leq 1 \mu D$), rejecting H_0 represents a false positive (Type 1 error), so the concept of power does not apply.

The probability that H_0 is rejected (with $\Delta pI_{measured} > \Delta pI_{measured_{crit}}$) for a given caprock permeability value, k_{ci} ($k_{ci} > 1 \mu D$) is the expected fraction of measurements that exceed $\Delta pI_{measured_{crit}}$, where this expectation is calculated across the 1000 simulations for that caprock permeability value, k_{ci} :

$$\begin{aligned} Power(k_{ci}) &= Prob[\Delta pI_{measured} < \Delta pI_{measured_{crit}} | k_{ci}] \\ &= \frac{1}{1000} \sum_{i=1}^{1000} F_{\Delta pI_{measured}}(\Delta pI_{measured_{crit}} | a_{Ii}, b_I) \end{aligned}$$

(6)

where $F_{\Delta pI_{measured}}(\Delta pI_{measured_{crit}} | a_{Ii}, b_I)$ is the lognormal cdf of $\Delta pI_{measured}$, evaluated at the value of $\Delta pI_{measured_{crit}}$, with lognormal parameters given by a_{Ii} and b_I , as specified in Equation 1.

3.3. Evaluating the influence of input parameters

The parameters listed in Table 1 and 2 serve as a baseline case, representing typical parameter values and a nominal level of uncertainty assumed to apply to a particular reservoir application. To illustrate the sensitivity of model predictions to variations in selected assumptions and parameters, we consider alternative monitoring time t , monitoring locations r , an increased CO_2 injection rate Q , and reductions in the magnitude of the assumed uncertainty of the reservoir properties in Table 2 (as might occur as a result of additional site characterization studies), computing how these alternative assumptions affect simulation results and the probability of each caprock permeability class that is inferred from an observation of ΔpI . The baseline monitoring time is at $t = 5$ year after the injection begins; ΔpI values at $t = 1$ year and $t = 10$ year are also simulated to explore the sensitivity of results to monitoring time. The baseline monitoring location is $r = 500$ m from the injection well, and we also present simulation results for locations at $r = 100$ m from the injection well. The injection rate is doubled from the baseline case $Q = 1$ MT- CO_2 /yr to 2 MT- CO_2 /yr. The uncertainty of the reservoir properties (i.e. the thickness, permeability and porosity of the injection zone and the above zone) is characterized by the variance of each distribution described in Table 2. Here, we evaluate the influence of reduced reservoir uncertainty by reducing the variance of each reservoir property (listed in Table 2) by half.

4. Results

4.1. Inferred caprock permeability class

The prior values of ΔpI across the four CPC simulations extend over the range $\sim 10^{-4}$ MPa– 45 MPa. Since the Bayesian update in Equation 4 assigns zero posterior probability wherever the prior probability is zero, this prior range for ΔpI determines the posterior domain as well. As the results below 0.01 MPa in the simulation runs are very inaccurate, the posterior domain of ΔpI is further chosen to be from 0.01 MPa to 45 MPa. Figure 3 shows the posterior probability of each CPC as a function of the observed $\Delta pI_{\text{measured}}$, for monitoring conducted at a) low measurement error (c.v. = 0.2); b) medium measurement error (c.v. = 0.3); and c) high measurement error (c.v. = 0.5), all at a monitoring location $r = 500$ m away from the injection well and at $t = 5$ year.

In Figure 3, the green line represents the posterior probability that an impermeable caprock is present. Other lines represent the probabilities that a permeable caprock (i.e. a leaky caprock) of varying degree are present. Generally, as the $\Delta pI_{\text{measured}}$ value decreases, the probability of an impermeable caprock decreases and it is more likely that an increasingly leaky caprock is present. For example, in the low measurement error case, with a $\Delta pI_{\text{measured}}$ value of 10, the probability of an impermeable caprock is 0.996; while with $\Delta pI_{\text{measured}} = 1$, the probability that an impermeable caprock is present is only 0.386 and the probability of a caprock with moderate permeability has reached a value of about 0.6. At low measurement error, the posterior

probability curves exhibit fluctuations at some $\Delta pI_{measured}$ values. This occurs in part due to discrete (non-overlapping) ranges of permeability associated with each of the four CPC classes. Nonetheless, the local fluctuation in the predicted posterior probability is small enough that it does not affect the predicted dominant CPC class. As the measurement error increases, the local fluctuations are dampened and the posterior probability curves become both broader and smoother.

a)

b)

Figure 3 Posterior distribution of caprock permeability class monitored at $r = 500$ m; $t = 5$ year and a) low measurement error ($c.v. = 0.2$); b) medium measurement error ($c.v. = 0.3$); c) high measurement error ($c.v. = 0.5$). $\Delta pI(measured)$ is the measured pressure buildup in the injection

zone. Critical values of $\Delta pI(\text{measured})$ at $\alpha = 0.05$ are computed from the impermeable (green curve) cases as: a) 0.0224 MPa; b) 0.0225 MPa; and c) 0.0211 MPa.

4.2. Results of Power Analysis

The power analysis is implemented using the method described in Section 3.2. The value of $\Delta pI_{\text{measured critical}}$ in Equation 6 depends on the value of α chosen for the test of hypothesis in Equation 5; lower values of α require stronger evidence that H_0 is false (i.e., a lower P-value) before it is rejected, dictating a lower value of $\Delta pI_{\text{measured}}$. As such, there is a lower probability of rejection of H_0 as α decreases, and as a result, less power.

The results of the power calculation for the case with medium measurement error (c.v. = 0.3) and with $\alpha = 0.1, 0.05$ and 0.01 , at the location $r = 500$ m away from the injection well and at $t = 5$ year, are shown in Figure 4. For a moderately leaky caprock with permeability $k_c = 10 \mu\text{D}$ and a moderate level of measurement error (c.v. = 0.3), the simulated statistical detection power of the pressure monitoring is still below 0.1 even at the significance level $\alpha = 0.1$. The detection power increases to values of 0.6 as k_c reaches approximately $400 \mu\text{D}$ at $\alpha = 0.05$, with the power further increasing to 0.9 at $k_c \sim 800 \mu\text{D}$. As such, very high caprock permeability is required before pressure monitoring as prescribed in this simulation will yield a high probability of detecting deviations from the baseline, impermeable assumption.

Figure 4 Power relationship indicating probability of leakage detection for permeable caprock, (i.e. caprock permeability value, $k_c > 1 \mu\text{D}$) with medium measurement error (c.v. = 0.3), $\alpha =$

0.1, 0.05 and 0.01 respectively, monitoring at a location $r = 500$ m away from the injection well, and $t = 5$ year.

4.3. Sensitivity analysis of assumed input parameters

The following sensitivity analyses were conducted to determine how model inferences are affected by changing the monitoring time (base case $t = 5$ year), the monitoring location (base case $r = 500$ m from injection well); the CO₂ injection rate (base case = 1 MT-CO₂/yr); and the initial uncertainty in reservoir properties (base case specified by distributions in Table 2):

- Simulating the monitoring of pressures after injection for one year ($t = 1$ year) and after injection for ten years ($t = 10$ year);
- Simulating the monitoring of pressures at locations closer to the injection well ($r = 100$ m);
- Doubling the injection rate to 2 MT-CO₂/yr; and
- Reparameterizing the distributions in Table 2 so that their variances are reduced by a factor of two.

Figure 5 shows the posterior probability of each CPC as a function of the observed $\Delta pI_{measured}$, for monitoring conducted with medium measurement error (c.v. = 0.3) a) at $t = 1$ year and b) at $t = 10$ year. Figures 3b, 5a and 5b are very similar, which indicates that beyond the first year of continuous CO₂ injection, the additional system response has little effect on the inferred caprock permeability class. The calculation results at $r = 100$ m are shown in Figure S2 of Appendix B. As expected, for all the cases considered, the lower the value of $\Delta pI_{measured}$, the higher the probability that the caprock is permeable. Furthermore, for a given value of $\Delta pI_{measured}$ the predicted most likely (dominant) caprock permeability class remains the same across monitoring locations. However, the location can affect the predicted probability of different caprock permeability classes.

The effects of a doubled injection rate and reduced uncertainty are summarized in Figure 6a and b, respectively, for classification of CPC's as a function of $\Delta pI_{measured}$, and in Figure 7a and b, respectively, for the statistical power to infer a permeable caprock ($k_c > 1 \mu D$) at different caprock permeability values. The base case monitoring location ($r = 500$ m) and medium measurement error are assumed, with pressure measured at $t = 5$ year. Comparing the curves in Figure 6a to those in Figure 3b suggests that doubling the injection rate has an effect on the predicted probabilities of different CPC's as a function of $\Delta pI_{measured}$. The green curve for the impermeable CPC (Figure 6a) starts to decrease at a higher value of $\Delta pI_{measured}$. Likewise, a doubling of the injection rate yields an increase in the statistical power for inferring a permeable caprock. This is as would be expected – increasing the injection rate increases the likelihood of leakage and a lower $\Delta pI_{measured}$, yielding a more likely detection of a permeable caprock.

Halving the uncertainty in reservoir properties in Table 2 yields significant differences in results, with tighter CPC curves exhibited in Figure 6b (compared to Figure 3b), implying greater resolution of the CPC for a given value of $\Delta pI_{measured}$. As a result, the statistical power to properly detect a permeable caprock increases significantly for $k_c > 100 \mu D$ (see Figure 7b).

a)

b)

Figure 5 Posterior distribution of caprock permeability class monitored with medium measurement error (c.v. = 0.3) a) at $t = 1$ year; b) at $t = 10$ year. $\Delta pI(measured)$ is the measured pressure buildup in the injection zone.

Figure 6 Posterior distribution of caprock permeability class at $r = 500$ m, $t = 5$ year and medium measurement error (c.v. = 0.3) a) at doubled injection rate ($Q = 2$ MT- CO_2/yr); b) at reduced reservoir uncertainty. $\Delta pI(\text{measured})$ is the measured pressure buildup in the injection zone.

a)

b)

Figure 7 Comparison of the detection power for a) doubled injection rate case with baseline injection rate case; b) reduced half reservoir uncertainty case with assumed reservoir uncertainty case at $r = 500$ m, $t = 5$ year, $\alpha = 0.05$, and medium measurement error (c.v. = 0.3).

5. Discussion

The principal purpose of this paper is to provide a proof of concept for statistically-based CO₂ leak detection using pressure monitoring supported by reservoir modeling. In addition, we have elucidated the factors that affect the inferences that can be made using the method. Reducing the uncertainty in reservoir properties is shown to allow caprock permeability classification to be made with greater resolution and power. At CO₂ sequestration sites, reservoir properties are usually quantified by site characterization activities (Chadwick et al., 2004; Chiaramonte et al., 2007). In addition to traditional site characterization techniques, including geological mapping, geophysical imaging, core analyses and hydraulic well testing, data collected during the initial CO₂ injection from monitoring techniques, such as crosswell seismic imaging and sampling fluid at an observation well, can be employed to better characterize reservoir properties (Doughty et al., 2007). Combining analysis of the potential for these characterization efforts to reduce uncertainty in site properties with statistical evaluation of ongoing monitoring, such as those presented in this study, can help to better quantify the value of information achieved by better site characterization.

Whether these results indicate that the sole use of pressure monitoring for leak detection at actual sites will be insufficient remains to be seen, though further application of this method with more

sophisticated reservoir models and site assumptions should allow this question to be explored with greater insight. Further analysis should also consider the joint application of multiple monitoring methods and tools, since a combination of methods will likely result in improved power. Complementary monitoring techniques, such as seismic monitoring, surface deformation monitoring, tracer monitoring, and groundwater chemistry monitoring are promising candidates to be employed for this purpose.

6. Conclusions

A Bayesian classification methodology is developed to infer the caprock permeability class, as a surrogate for potential CO₂ leakage at a geologic sequestration site, using the expected distribution of pressure increases in the injection zone for permeable vs. impermeable caprock cases. The detection power of pressure monitoring is evaluated using a Bayesian formulation that considers uncertainty in site conditions, Monte Carlo simulation results for modeled injection zone pressure profiles, and measurement errors for the corresponding pressure measurements. The results indicate that pressure monitoring alone is not sufficient to detect a permeable caprock for the system considered in this study, except for very high caprock permeability values. Time has little impact on the inferred caprock permeability class and the detection power of pressure monitoring. The injection rate has an influence on the predicted caprock permeability class and the detection power of the simulated pressure monitoring. Higher confidence in the predicted caprock permeability class and a significant improvement in the statistical detection power for a leaky caprock can be achieved by reducing the uncertainty in reservoir properties through further site characterization. Other monitoring techniques, such as seismic monitoring, surface deformation monitoring and groundwater chemistry monitoring, may need to be combined with pressure monitoring to conduct CO₂ leakage detection monitoring with high confidence.

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Figure Captions:

Figure 1 Schematic diagram of the simplified geological model, adapted from Neuman and Witherspoon (1969).

Figure 2 Simulated uncertainty in pressure buildups in the injection zone at 500 m from point of injection after injecting CO₂ with a) Caprock permeability $k_c = 0.1 \mu\text{d}$; b) Caprock permeability $k_c = 1 \mu\text{d}$; c) Caprock permeability $k_c = 10 \mu\text{d}$; and d) Caprock permeability $k_c = 100 \mu\text{d}$. Results shown are the median (solid line), 5th and 95th percentile values (dashed lines) of 1000 Monte Carlo simulations for the injection zone (ΔpI : pressure buildups in the injection zone, shown in red).

Figure 3 Posterior distribution of caprock permeability class monitored at $r = 500 \text{ m}$; $t = 5 \text{ year}$ and a) low measurement error (c.v. = 0.2); b) medium measurement error (c.v. = 0.3); c) high measurement error (c.v. = 0.5). $\Delta pI(\text{measured})$ is the measured pressure buildup in the injection zone. Critical values of $\Delta pI(\text{measured})$ at $\alpha = 0.05$ are computed from the impermeable (green curve) cases as: a) 0.0224 MPa; b) 0.0225 MPa; and c) 0.0211 MPa.

Figure 4 Power relationship indicating probability of leakage detection for permeable caprock, (i.e. caprock permeability value, $k_c > 1 \mu\text{D}$) with medium measurement error (c.v. = 0.3), $\alpha = 0.1, 0.05$ and 0.01 respectively, monitoring at a location $r = 500 \text{ m}$ away from the injection well, and $t = 5 \text{ year}$.

Figure 5 Posterior distribution of caprock permeability class monitored with medium measurement error (c.v. = 0.3) a) at $t = 1 \text{ year}$; b) at $t = 10 \text{ year}$. $\Delta pI(\text{measured})$ is the measured pressure buildup in the injection zone.

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Table 1 Fixed reservoir and injection conditions assumed in Monte Carlo uncertainty analysis

625 Table 2 Distributions of uncertain input parameters assumed in Monte Carlo uncertainty analysis
626 (based on values found in the National Petroleum Council database (NPC, 1984))

627 a: The mean and standard deviation values are parameters of the lognormal distribution in base 10, that is,
628 the mean and standard deviation of the base 10 logarithm of the variable before truncation.

629 b: The mean and standard deviation values are parameters of the normal distribution before truncation.

630

631 Table 3 Intervals of caprock permeability values representing different leakage levels

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