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Pressure management via brine extraction in geological CO_2 storage: adaptive optimization strategies under poorly characterized reservoir conditions

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Pressure Management via Brine Extraction in Geological CO_2 Storage: Adaptive Optimization Strategies under Poorly Characterized Reservoir Conditions

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Abstract

Industrial-scale injection of CO_2 into the subsurface increases the fluid pressure in the reservoir, which if not properly controlled can potentially lead to geomechanical damage (i.e., fracturing of the caprock or reactivation of faults) and subsequent CO_2 leakage. Brine extraction is one approach for managing formation pressure, effective stress, and plume movement in response to CO_2 injection. The management of the extracted brine can be expensive (i.e., due to transportation, treatment, disposal, or re-injection), with added cost to the carbon capture and sequestration (CCS); thus, minimizing the volume of extraction brine is of great importance to ensure that the economics of CCS are favorable. The main objective of this study is to demonstrate the use of adaptive optimization methods in the planning of brine extraction and to investigate how the quality of initial site characterization data and the use of newly acquired monitoring data (e.g. pressure at observation wells) impact the optimization performance. We apply an adaptive management approach that integrates monitoring, calibration, and optimization of brine extraction rates to achieve pre-defined pressure constraints. Our results show that reservoir pressure management can be extremely benefited by early and high frequency pressure monitoring during early injection times, especially for poor initial reservoir characterization. Low frequencies of model calibration and optimization with monitoring data may lead to optimization problems, because either pressure buildup constraints are violated or excessively high extraction rates are proposed. The adaptive pressure management approach may constitute an effective tool to manage pressure buildup under uncertain reservoir conditions by minimizing the volumes of extracted brine while controlling pressure buildup.

Keywords: CO_2 storage, pressure management, fault activation, caprock fracturing, parameter uncertainty, brine extraction

1 Introduction

Injection of CO_2 into the subsurface at industrial scale can result in significant fluid pressure increase in a reservoir, which can be a limiting factor for sequestration capacity in saline aquifers (Zhou and Birkholzer, 2011; Thibeau et al., 2014). The possibility of distant pressure-related impacts need to be considered, which if not properly controlled can lead to potential environmental impacts (Zhou and Birkholzer, 2011). These potential environmental concerns include groundwater contamination (Apps et al., 2010; Birkholzer et al., 2009) stemming from pressure-driven brine leakage through conductive pathways, such as improperly plugged abandoned wells or distant faults (Metz et al., 2005), and the potential for fault reactivation and possibly seal breaching (Morris et al., 2011; Rutqvist et al., 2007). Large areas with pressure increases can also require more complex and costly site characterization and monitoring (US EPA, 2008; Oldenburg et al., 2016).

Concerns about local- or regional-scale pressurization have motivated research on engineering approaches for subsurface pressure control, usually involving some strategies of extracting resident brines from a storage reservoir while CO_2 is injected. The potential benefits of employing brine extraction wells to manage pressure in the reservoir include reduced stress on the sealing formation, reduced risk of brine and CO_2 intrusion into other formations, increased storage capacity, and reduced area of review for regulatory assessment (Birkholzer and Zhou, 2009). In recent years, pressure management approaches via brine extraction have been studied in generic modeling exercises to demonstrate the proof of concept and feasibility (e.g. Bergmo et al., 2011), but so far brine extraction has not been used in actual geological carbon storage (GCS) projects, mainly because the currently injected CO_2 volume are limited and large-scale pressure increases are rare. However, for large-scale projects expected in future GCS deployment, modeling analyses reveal that brine extraction can be very beneficial and in some cases necessary, enhancing storage capacity and injectivity (Buscheck et al., 2012; Buscheck et al., 2014; Pongtepupathum et al., 2017; Ziemkiewicz et al., 2016) and reducing risk of environmental impacts and induced seismicity (Birkholzer et al., 2012). For example, the industrial-scale Gorgon CO_2 storage project in Australia considered the possibility of brine extraction through four wells located to the west of the site (Flett et al., 2008; Greig et al., 2016; Liu et al., 2013).

Ensuring safety and robustness against failure is critical and must be integrated into actual GCS projects (Harp et al., 2017). ‘A factor of safety’ is a concept applied in all engineering applications. In our work we assumed that the threshold values for critical pressures already include the factor of safety. The main goal of this study is to investigate the influence of two factors on the extraction rates of brine for pressure management. These two factors are i) the quality of data of the initial site characterization, and ii) the frequency of model calibration and optimization calculations based on newly acquired monitoring data.

In preparation for deployment of future large-scale GCS projects, the U.S. Department of Energy (DOE) created the Brine Extraction and Storage Test (DOE-BEST) program to evaluate the technical feasibility of managing subsurface pressures associated with large-scale CO_2 injection volumes and to assess the cost and effectiveness of desalination technologies for saline waters containing high total dissolved solids (TDS). Two projects funded under this program are currently in the final planning and design phase. The projects will demonstrate management of reservoir pressure through brine extraction in actual field settings and test desalination approaches for the utilization of the extracted brines (DOE, 2016).

Recognizing the potential management cost of extracted brine (Harto and Veil, 2011), recent work by Birkholzer et al. (2012) and Cihan et al. (2015) aimed to develop flexible optimization methods for pressure control, with the goal of minimizing the volume of extracted brine while maximizing CO_2 storage and meeting other constraints needed for safe and efficient GCS operations. For given pressure constraints, such as the maximum allowable pore pressure along a critically stressed fault, the optimization algorithm finds optimal solutions for placement of extraction wells and transient pumping rates. Example applications of optimization algorithms to hypothetical CO_2 storage scenarios in realistic field settings demonstrate that strategic extraction can achieve a significant reductions in the total volume of extracted brine while limiting pressure increases (Cihan et al., 2015).

The knowledge of subsurface properties is always incomplete. Especially during the planning stages of CO_2 projects, site characterization data are often quite limited and there are large uncertainties in rock properties. Thus, predictive models for the reservoir conditions upon CO_2 injection are initially associated with large model uncertainties. These models can be improved through calibration using monitoring data obtained during the operation of the projects. Based on new data received and subsequent improvement of the existing models, optimization calculations may then need to be revised and operational decisions for controlling and managing subsurface pressurization may need to be updated. The oil industry commonly uses the so-called "closed-loop" approach, which includes optimization and model-updating algorithms for reservoir management (Aitokhuehi and Durlofsky, 2005; Sarma et al., 2006). Observations such as well-log measurements, production rates (oil, gas, and water), and 4D seismic data are collected to improve knowledge of uncertain parameters and then used to improve the prediction of reservoir simulation models (Evensen et al., 2007; Nævdal et al., 2005; Skjervheim et al., 2005).

The goal of this study is to apply an adaptive management approach that combines monitoring + inversion + optimization in an integrated framework for pressure control in GCS applications. We use this framework to develop and implement a pressure management strategy at a hypothetical site. In terms of geological setting and well configurations, the hypothetical example resembles one of the DOE-BEST projects, which will provide a testbed for demonstrating adaptive pressure management. However, the spatial and temporal scales of the hypothetical scenario investigated in this study are much larger than the planned field test scenario in this DOE-BEST project. It is important to note that the actual DOE -BEST project demonstration site has no known faults, whereas the hypothetical scenario reported here includes a critically stressed hypothetical fault which needs to be protected from hypothetical reservoir pressure increases.

Using the hypothetical injection application as an example case, we focus on testing and demonstrating an adaptive management approach to understand the influence of two factors on the optimized extraction rates for pressure management. These factors are: 1) the quality of data obtained during the initial site characterization such as hydraulic properties of the reservoir system, and 2) the frequency of model calibration and optimization calculations based on newly acquired monitoring data. Our objective is to demonstrate that adaptive management can effectively manage pressure effects associated with fluid injection, such as the potential for inducing seismic events and leakage along hypothetical faults, and that it can do so under realistic conditions where reservoir data are uncertain. The management strategy that we use for the hypothetical site combines two complementary brine extraction methods: (1) “active” extraction of brine from the injection reservoir to the surface with optimized time-varying pumping rates, and (2) “passive” pressure relief, which relies on the pressure increase in the injection reservoir to provide the driving force for resident brine to flow through a relief well; in this case, transferring fluids into suitable deeper geological layers than the injection layer (Figure 1). The advantage of “passive” pressure relief is that once a relief well is drilled and completed there are no additional costs for brine pumping or handling, in contrast to “active” extraction. The disadvantage is that “passive” brine extraction cannot be optimized to the project needs; the brine volume transferred out of the storage reservoir into other formations is a function of their pressure differentials. For this same reason, "passive" brine extraction requires that the receiving units are not overpressurized to the point where they cannot passively receive the brine.

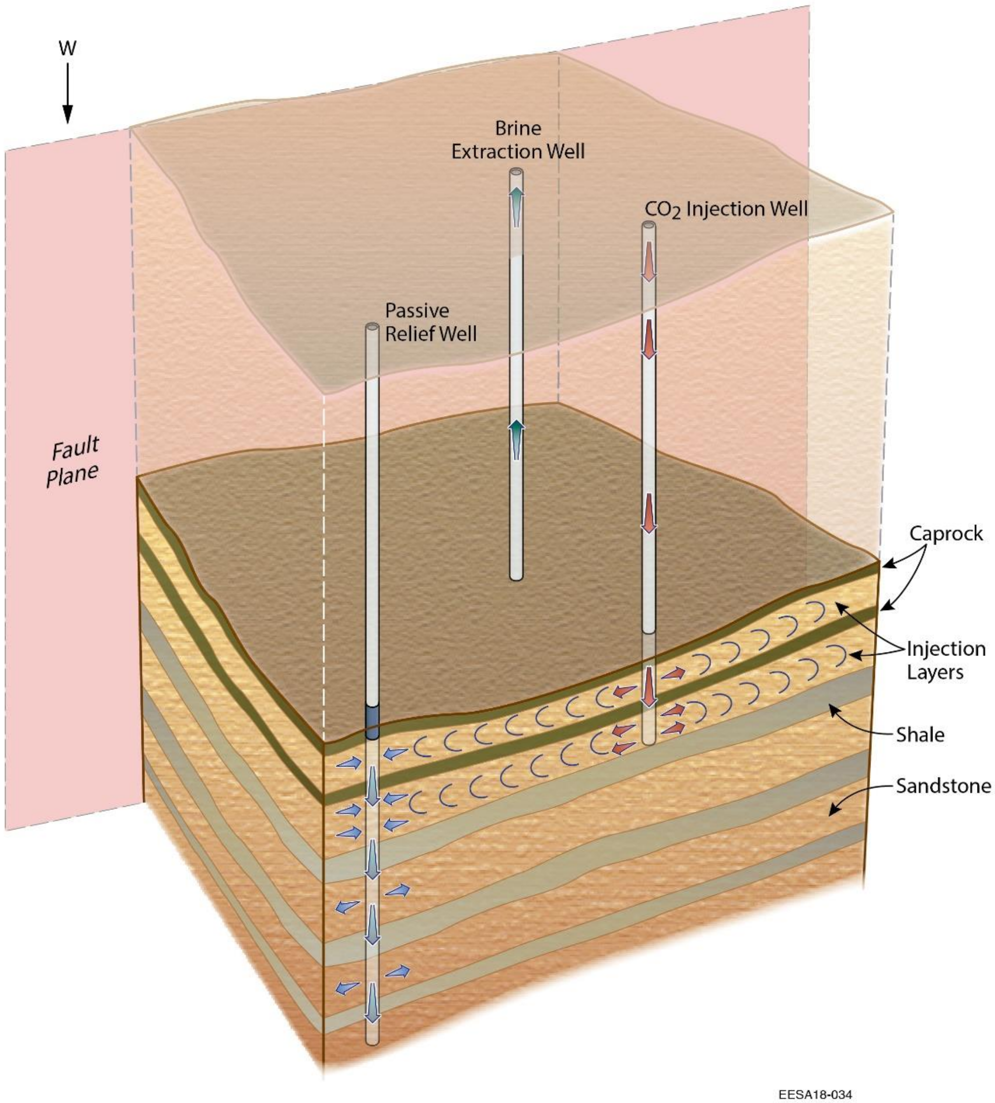

Figure 1. Schematic showing the pressure management strategy in this study to reduce risk of caprock failure and risk of fault reactivation. The schematic shows the five top aquitards as well as the five top aquifers of Table 1(from 22 to 18). Injection of CO_2 occurs into two reservoir layers (aquifers 22 and 21 in Table 1). Brines are extracted from two wells, one of them "actively" pumping to the surface, the other "passively" moving brines into deeper layers. The back of the schematic figure shows a hypothetical critically stressed fault, for which a maximum allowable pressure change has been defined. Another pressure limit is defined to avoid caprock damage.

The paper is organized as follows. Section 2 presents brief descriptions of the adaptive management methodology, the reservoir modeling approaches, the optimization and calibration problem solved, and selected scenarios of the adaptive management approach. In section 3 and section 4, the results of the sensitivity analysis of site characterization are presented and discussed. Section 5 summarizes the main conclusions of this study.

2 Adaptive management approach

Adaptive management involves (1) analysis and interpretation of monitoring data acquired during the field test, (2) reservoir model testing, (3) updating of model parameters using inverse modeling methods, and (4) revised optimization plus, if necessary, modification of reservoir management schemes (i.e., time-dependent extraction rates, changes in extraction schemes) based on the updated reservoir model predictions. In this study, we use a computer algorithm that automatically accomplishes the steps above at a selected frequency to estimate future minimum extraction rates based on the existing reservoir model.

The initial reservoir model, based on available site characterization data, is used to estimate the initial and future minimum extraction rates that provide acceptable pressure conditions. These acceptable conditions, or pressure constraints need to be defined before the start of the optimization. An optimization algorithm coupled to the reservoir model then generates optimal extraction rates that may vary during the project period (Stage 1). Depending on the reservoir conditions, extraction may not need to start at the beginning of injection in most cases. However, if the initially estimated values are not zero, the extraction well(s) start pumping using the calculated initial extraction rate(s). As soon as newly acquired data become available during the operation (e.g., pressure changes at the observation wells, geophysical measurements), the model predictions are compared against the observations (Stage 2). If the model predictions are significantly different from the observations, which is typically the case, especially during early operation, then the reservoir model is updated or recalibrated with the new data using an inverse modeling tool (Stage 3). After the model calibration process, the algorithm goes back to Stage 1 to estimate new optimal extraction rates at the current and future times that satisfy the constraints based on the predictions with the existing model. The extraction well(s) continue operating at the current extraction rate until new data are analyzed and the model and extraction rates are updated. The adaptive management algorithm may continue to be used throughout the injection and perhaps post-injection phase to ensure that the extraction rates are minimized and pressure constraints are met.

2.1 Reservoir flow model

For this study, a multilayered reservoir model was constructed using the existing well logs, lithologic logs, sidewall core data, and well test data gathered from an existing well near the DOE-BEST project field site. The targeted reservoir system is a thick (about 700 m) sequence of very porous and permeable fluvial and fluvial deltaic sandstones alternating with shale. Injection occurs only into the upper two sandstone layers at a total rate of 1,090 m^3/d (~ equivalent to about 0.3 Mt of CO_2 injection) over 30 years. We assume that there is a concern about caprock fracturing and potential fault slip due to increased pressures near the injection well and along a hypothetical fault which is a few kilometers away from the injection well. We furthermore assume that the critical pressure changes for caprock fracturing and fault slip are $\Delta P_{crt,c}$ = 8 MPa and $\Delta P_{crt,f}$ = 0.4 MPa, respectively. As mentioned before, the pressure management strategy involves a passive relief well and an active extraction well to control pressure changes (see Figure 1).

To efficiently simulate the fluid flow and pressure changes in the reservoir system, we employ a semi-analytical model for single-phase flow in multilayered systems that has capabilities to represent multiple injection/extraction and leaky wells, diffuse flow through aquifer-aquitard interfaces, and focused brine leakage or flow through leaky wells (Cihan et al. 2011). We approximate the target reservoir with its sandstone and shale layers as aquifers and aquitards, respectively, where fluid flow is assumed horizontal in the aquifers and vertical in the aquitards. Initially, hydrostatic pressure is assumed for the whole system of aquifers and aquitards. Each aquifer and aquitard may have different hydraulic properties and thicknesses; however, within each aquifer and aquitard, properties and thickness remain uniform. Leaky wells are represented as Darcy-type flow pathways with segment-wise property variations (e.g., well radii, permeability, screened/cased in well-aquifer segments, plugged/unplugged in well-aquitard segments). The segments correspond to intersections of each well with individual layers of the multilayered system. Further details of the semi-analytical solution approach and a description of the computer program to compute the solution in terms of pressure changes can be found in Cihan et al. (2011). The leaky well feature of the semi-analytical model is particularly useful for this study to represent the passive relief well in our hypothetical scenario. Table 1 lists the identified 22 aquifer and 22 aquitard layers (from bottom to top) of the target reservoir system with their hydraulic properties including thickness, hydraulic conductivity and specific storativity. Aquifer Layers 21 and 22 (top two aquifer layers) are the injection layers.

Table 1. Reference ('true') hydraulic property values of reservoir layers containing aquifers alternating with aquitards. The bottom layer is an aquifer, and the top layer is an aquitard.

Aquifers				**Aquitards**			
Layer	Thickness (m)	$\boldsymbol{K}=K_{xx}$ (m/d)	$S=S_s$ (m^{-1})	Layer	Thickness (m)	$\boldsymbol{K'}=K_{zz}$ (m/d)	$S'=S_s$ (m^{-1})
1 (bot)	42.062	0.176	1.856E-06	1	6.706	4.729E-04	1.065E-06
2	18.288	0.207	2.025E-06	2	6.096	1.537E-03	1.081E-06
3	10.973	0.674	2.025E-06	3	6.706	4.032E-03	1.452E-06
4	29.261	0.237	1.940E-06	4	7.925	6.706E-04	1.162E-06
5	8.534	0.144	1.856E-06	5	18.593	1.889E-03	1.065E-06
6	30.785	0.182	1.680E-06	6	10.973	1.548E-03	1.743E-06
7	15.850	0.670	2.000E-06	7	9.449	3.124E-03	1.355E-06
8	23.470	0.498	2.001E-06	8	14.021	1.809E-03	1.150E-06
9	13.106	0.871	1.990E-06	9	5.791	1.059E-03	1.162E-06
10	16.459	0.447	2.025E-06	10	9.144	3.859E-03	1.452E-06
11	9.144	0.321	2.025E-06	11	8.534	4.960E-03	1.020E-06
12	3.048	0.826	1.940E-06	12	7.315	2.301E-03	1.258E-06
13	23.165	0.284	1.940E-06	13	1.829	1.462E-03	1.162E-06
14	10.973	0.338	2.025E-06	14	4.572	1.896E-03	1.646E-06
15	34.138	0.720	3.122E-06	15	12.192	5.159E-04	5.808E-07
16	55.778	0.195	2.025E-06	16	9.449	1.032E-03	1.936E-06
17	3.962	1.032	3.037E-06	17	2.438	6.190E-04	1.452E-06
18	14.021	0.037	2.278E-06	18	12.192	5.732E-03	2.420E-06
19	46.634	0.273	2.607E-06	19	3.962	5.159E-05	8.713E-07
20	23.165	0.403	2.563E-06	20	7.620	1.032E-03	1.646E-06
21	10.668	0.503	2.244E-06	21	2.438	2.053E-09	8.713E-07
22	3.048	0.375	2.306E-06	**22 (top)**	86.563	4.769E-04	1.258E-06

In actual field demonstrations, higher-fidelity numerical models are typically more appropriate, but in this demonstration application, we prefer using the semi-analytical solution to be able to conduct ultrafast model calibration and optimization calculations within the adaptive management framework. Brine flow and pressure changes along the far-field fault and brine flow through the passive well outside the CO_2 plume zone can be described reasonably well by the single-phase flow models —without considering local two-phase and variable density effects— simply by representing the injection of CO_2 as an equivalent volume of saline water (Nicot 2008;

Cihan et al., 2013). However, Cihan et al. (2013) showed that the analytical solution for single-phase brine flow would slightly overpredict pressure buildup within the CO_2 plume zone, compared to the multiphase simulator TOUGH2/ECO$_2$N (Pruess 2005). This in turn leads to slightly higher brine extraction rates, calculated by the optimization algorithm, than actually required. Thus, we may consider the optimization results based on the analytical model to be on the conservative side.

2.2 Optimization

The specific goal of the optimization in this study is to minimize the volume of extracted brine while effectively controlling pressure buildup such that (1) the caprock fracturing pressure is not exceeded, and (2) reactivation along a hypothetical fault near the injection location can be avoided. (These pressure constraints are a proxy for any other pressure constraints one may need to define in a given project.) If the total volume of injected fluid is V_{inj}, and the total volume of extracted fluid is V_{ext}, then the goal is to minimize the extraction ratio defined by V_{ext}/ V_{inj}. Costs associated with the pumping per volume of injected or produced fluid and treatment of extracted brine are assumed to be proportional to the extraction ratio defined in Eq. (1). Formally, the specific optimization problem that involves the objective function and the constraints, respectively, can be expressed as:

$$\text{Minimize } f(\boldsymbol{p}) = V_{ext}/V_{inj} \tag{1}$$

$$\text{Subject to} \quad g_1(\boldsymbol{p}) = max\{\Delta P(x_{obs}, t)\} - \Delta P_{crt,f} < 0, \tag{2}$$

$$g_2(\boldsymbol{p}) = max\{\Delta P(x_{obs}, t)\} - \Delta P_{crt.c} < 0$$

where $\boldsymbol{p}$ is the parameter vector that may include constant or time-dependent function parameters for controlling extraction rates and, in the most general case, the number and locations of extraction wells if one decides to have the algorithm select an optimal well design. For this study, we assume that the location of extraction wells is known, and that the extraction rate(s) are optimized as piece-wise time-dependent parameters. The two constraints in Eq. (2) represent the pressure management goal of keeping reservoir pressure increases in defined impact zones below critical pressure buildup values (with respect to the pressure prior to the injection, $\Delta P(t)=P(\text{t})-P(t=0)$). We assume in the first constraint (g_1) that the fault slip risk becomes too high if the pressure buildup at any location in the impact zone (hypothetical fault) exceeds $\Delta P_{crt,f}$. Pressure buildup along the impact zone is recorded through a vector of observation points ($\boldsymbol{x}_{obs}$), as many as required. In addition to the pressure buildup constraint along the fault, we take into account the fracturing pressure constraint (g_2) near the injection well ($\Delta P_{crt,c}$).

To solve the optimization problem, we apply a constrained differential evolution (CDE) algorithm modified from a differential evolution algorithm (Deb, 2000; Cihan et al., 2015) within each step of the adaptive management framework. The CDE algorithm is particularly useful for solving global optimization problems involving well placement and dynamic injection/extraction control (e.g., Cihan et al., 2015). As mentioned above, we assume in this study that the well locations are known, and we employ CDE to solve only the problem of dynamic extraction control.

2.3 Calibration

The specific goal of the calibration in this study is to minimize the error between pressure measurements observed and pressure measurements generated with the simulations (Equation 3). For the inverse estimations conducted at each step of the adaptive algorithm, we use the same method (CDE) as in Stage 1 to inversely estimate unknown reservoir properties using observed hydraulic pressure buildups. With regards to monitoring data available in our hypothetical example, we assume that pressure measurements are made at each aquifer (22 aquifers) and at three locations: in the injection well, the active extraction well, and the passive relief well.

$$\text{Minimize } h(\boldsymbol{q}) = \sum_{1}^{N_{Obs}} \sum_{1}^{N_{Time}} \left(\frac{P(\boldsymbol{x},t) - P(\boldsymbol{x}_{obs},t)}{P(\boldsymbol{x}_{obs},t)} \right) \tag{3}$$

where $\boldsymbol{q}$ is the parameter vector that include the aquifer and aquitards properties to be calibrated, N_{Obs} is the equal to the number of locations (66 = 22*3), and N_{Time} is the number of observations along time.

The observation values are generated by using the true model with the reference properties in Table 1 and then these are compared with the observation values generated by the properties of the model.

2.4 Scenarios of the adaptive management framework

We employ the adaptive optimization framework to optimize the frequency in which data should be collected and how we could do to make this a better and safer site. For this purpose we study the effects of two factors on the optimized volume of extracted brine: 1) the quality of data obtained during the initial site characterization (e.g. hydraulic properties of the reservoir system), and 2) the frequency of model calibration and optimization calculations based on the monitoring data. Table 2 summarizes the different sensitivity scenarios for these two factors. By considering several levels of uncertainty for the initial property data of the reservoir system (over or under-estimated), we study their effects on the calculated values of the optimal brine extraction ratios in Eq. (1). Under uncertain initial reservoir conditions, we also investigate the effects of the frequency of model updates a on the performance of adaptive optimization. In the section 4, we present comparisons of the extraction rates calculated for ‘true’ reservoir properties versus the estimated ratios for 'uncertain' reservoir properties, with different-level initial guesses and different-frequency model updates.

Table 2. Scenarios considered for the adaptive management framework

Frequency of model update	**Deviations from the actual hydraulic properties**
Fixed frequencies of 30yr, 10yr, 6yr, 5yr, 3yr, and variable frequency (from 3 days at very early times to 3yr at late times)	Over and under-estimated properties at time=0: +20%, +40%, -20%, -40%

The uncertain hydraulic properties considered in this study are the hydraulic conductivity and specific storage parameters of one of the injection aquifers (Aquifer Layer 22) and corresponding overlying aquitard (Aquitard Layer 22). We select this layer because the pressure changes are most sensitive to their properties. The reservoir properties of the other aquifer layers (1-21) are tied to those of Aquifer Layer 22, and the properties of the other aquitard layers (1-21) are tied to those of Aquitard Layer 22, which reduces the number of unknowns from 88 to 4. Because of the petrological similarities of the aquitard layers, we can assume that the relative ratios of the estimated parameters can be assumed reasonably accurate for all aquifer layers and all aquitard layers, respectively. In other words, we can recalculate the reservoir properties of Aquifer and Aquitard Layers 1-21 based on the inversely estimated properties of Layer 22 (K_{22}, K_{22}', S_{s22}, S_{s22}'), assuming that parameter ratios are fixed (K_i/K_{22}, S_{si}/S_{s22}, K_i'/K_{22}', S_{si}'/S_{s22}', i=1,…,21, calculated using Table 1), where the prime sign indicates aquitard.

3. Results

3.1 Results without pressure management

We first present pressure results in the target reservoir for CO_2 injection without any pressure management. Figure 2 shows maximum pressure changes as a function of time near the well and along the fault in response to fluid injection at 1,090 m^3/d (~ equivalent to about 0.3 Mt of CO_2 injection) for 30 years into an injection zone at about 1,500 m depth from the surface. The injection zone corresponds to Aquifer Layers 21 and 22. The total injection rate is distributed into the two aquifer layers of the model proportionally according to their transmissivity values. Significant differences can be observed between the five reservoir property cases (i.e., true, -40%, -20%, +20%, +40%). In Figure 2a, the forward modeling results with under-estimated reservoir properties (-20% and -40%) indicate that the caprock pressure buildup constraint of 8 MPa can be reached very quickly as soon as the injection starts. The model results with over-estimated reservoir properties (+20% and +40%) show no risk of caprock failure, while the true model shows that the critical pressure buildup of fracturing the caprock is reached after about 22 years of injection. Figure 2b shows that fault slip can occur within about three to twelve years of injection for all reservoir property cases, under- or over-estimated. The estimated time for the constraint violation (fault pressure above 0.4 MPa) decreases with decreasing aquifer hydraulic conductivity values.

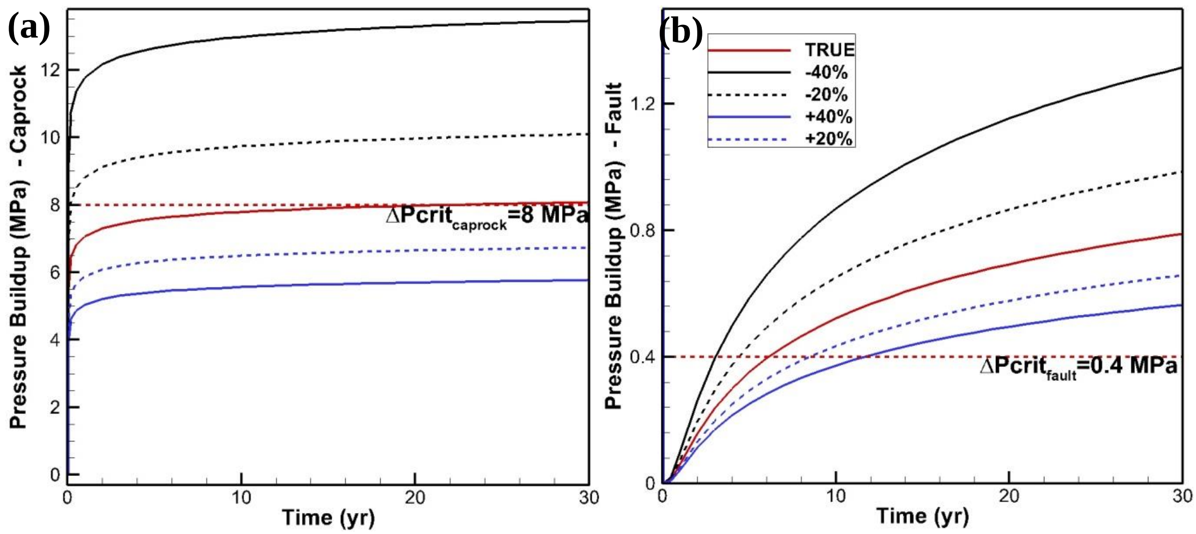

Figure 2. Profiles of maximum pressure buildup (in MPa) (a) at the caprock and (b) at the fault. (Note that Cihan et al.'s computer program (2011) produces the results in terms of head in meters, and to convert the head buildup to pressure buildup, we used a uniform brine density of 1126.026 kg/m^3.)

3.2 Results applying adaptive management approach

Figure 3 shows pressure buildup contours for the +20% case in Aquifer Layer 22 where the pressure buildup front has the largest extent compared to the other layers, for two pressure management scenarios: Figure 3a shows a simulation where only the passive relief well operates, which transfers brine from the injection reservoirs to deeper layers. Figure 3b shows results for a case where passive relief and active extraction operate together. In the first case, there is no optimization since the passive brine transfer depends only on the vertical pressure differential between injection layers and deeper layers. In contrast, the active brine extraction rates in Figure 3b are optimized to meet the given pressure constraints.

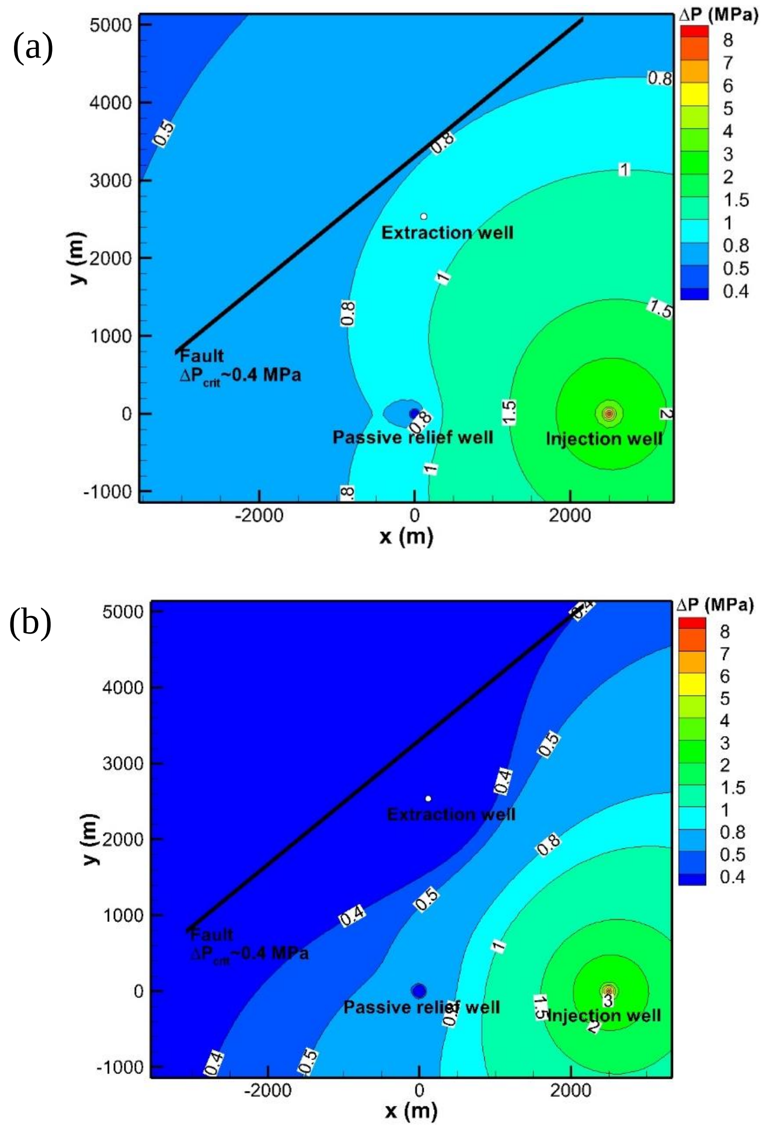

Figure 3. Pressure buildup contours (in MPa) at time=30 years with (a) only passive extraction and (b) passive and active extraction (updates every 3 years) for the +20% case in Layer 22.

As seen in Figure 3a, passive pressure relief alone is not sufficient to reduce the injection-induced pressure buildup below the desired critical value of 0.4 MPa near the hypothetical fault. Therefore, active brine extraction is needed to satisfy the pressure constraints, especially near the fault. With the objective of determining optimal dynamic extraction rates, we ran our automated adaptive optimization algorithm that starts with the different initial guesses of the reservoir properties (-40%, -20%, +20%, and +40%). For each of these cases, we also varied the model update frequency to understand its impact on the performance of the adaptive pressure management (Table 2). As a reminder, the monitoring data used for model calibration in this study are the pressure measurements at the top two aquifer layers of three wells (injection, passive relief, and extraction). We assume here that monitoring data collection and model update are conducted at the same frequency. In practice, monitoring data collection for pressure changes should be expected to be much more frequent than the model updates.

Figure 3b displays an example of a successful pressure management optimization for the +20% case where updates of the monitoring, calibration, and optimization steps occur every three years. When the adaptive management through active and passive extractions is applied, the pressure buildup along the fault is controlled and does not exceed the maximum critical pressure of 0.4 MPa at the end of the injection (time = 30 years). Despite the fact that the passive relief well alone as a pressure control approach is not sufficient for this scenario, its use together with the active extraction reduces the total volume of extracted brine by up to 20%. The benefit of using passive relief wells in reducing brine extraction volumes can vary depending on the magnitudes of the pressure buildup constraints and their distances from the injection well (Birkholzer et al., 2012).

Figure 4 summarizes the results of applying adaptive management to the different property and model calibration scenarios listed in Table 2. The figure shows the total extraction ratio (over the duration of the project) as a function of the model update and optimization frequency (Δt), starting with every three years up to 30 years. Cases that consider a model update frequency (Δt) of 30 years do not include monitoring or model update through calibration; they simply apply constant extraction rates optimized using the initial guesses.

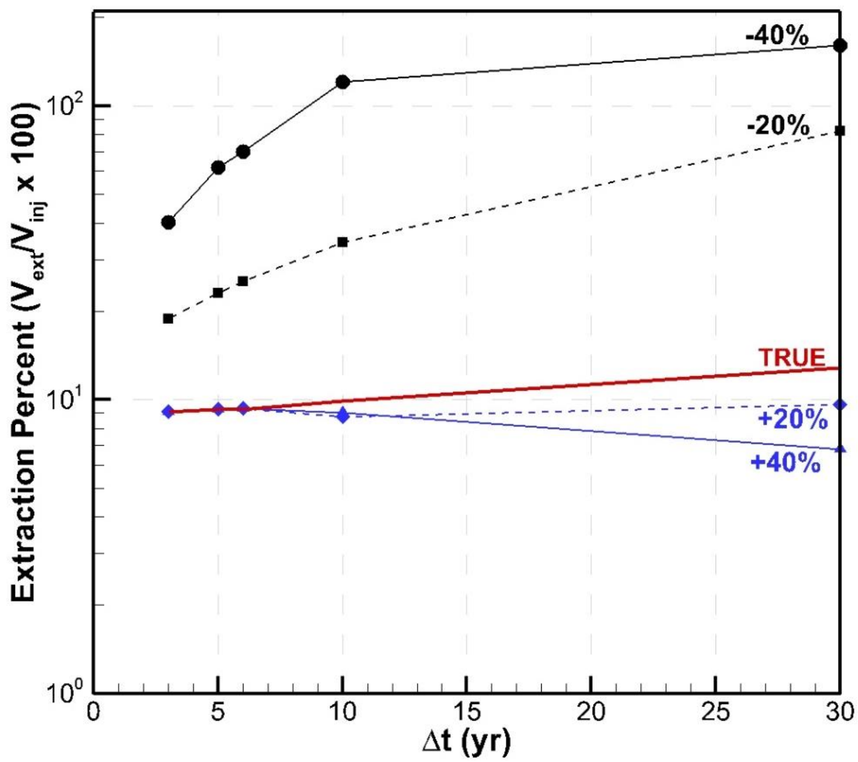

Figure 4. Summary of the adaptive optimization results: Variation of the estimated brine extraction ratio as a function of initial deviations from reservoir properties and model update frequency (Δt).

Figure 4 shows that for the reference scenario ('true' model), more frequent updates decrease the objective function from V_{ext}/V_{inj}=12.8% for Δt=30 years to V_{ext}/V_{inj}=9.1% for Δt=3 years. In this case, a better optimization is achieved when the extraction rates are updated every three years rather than operating with a constant extraction rate over 30 years. Optimization results are more complicated for the scenarios involving uncertain initial model properties, in which case the full monitoring + inversion + optimization cycle is conducted. For example, looking at the cases with under-estimated initial parameters (-20% and -40%), the calculated optimal extraction ratios are significantly higher than the actual optimal extraction ratios for all model update cases, in particular if the model updates are conducted less frequently. This occurs because the reservoir system is initially managed with a non-optimal model using the under-estimated reservoir properties, and it takes several iteration cycles to estimate more reliable reservoir properties with analyses of the monitoring pressure data. As the frequency of monitoring data analyses and model updates increases (moving to the left on the time axis in Figure 4), the calculated extraction ratios approach the true values. On the other hand, scenarios with over-estimated initial hydraulic properties have a lower value of V_{ext}/V_{inj} than the reference scenario; in other words, the extracted volume is under-estimated, specifically for cases with low frequency of updates (Δt>6 years); when the number of updates increases, the V_{ext}/V_{inj} approaches the true case. We show in Figure 5 that extracting less brine than necessary can result in *not* meeting the desired pressure constraints, i.e., possibly causing failure of the caprock or activation of the fault, a result of the inaccurate models used for optimization.

4 Discussion

4.1 Influence of initial hydraulic properties uncertainty

The potential impact of pressure management optimization with inaccurate models is shown in Figure 5 for all the cases of over- and under-estimated reservoir properties and a model calibration conducted every 10 years. This figure shows the evolution of the maximum pressure buildup at the injection well (Figure 5a) and near the fault (Figure 5b), compared to the respective pressure constraints for caprock failure and fault slip, respectively. Initially, the model prediction of the pressure changes is not accurate due to incorrect hydraulic properties and insufficient data collected. For the scenarios with under-estimated reservoir properties (-40% and -20%), the extraction rates are over-estimated because the pressure buildup in the reservoir is over-estimated; thus, the optimization assumes that more brine extraction is needed to stay below the caprock fracturing pressure buildup at the injection well. As a result of these excessively high extraction rates specifically within the first ten years, the reservoir pressure near the injection well remain significantly lower than the pressure limit for caprock fracturing, a safe but also costly practice. In contrast, for scenarios with over-estimated initial hydraulic properties (+20% and +40%), the extraction rate calculated by the optimization is significantly under-estimated. As a result, the observed pressure buildup at the fault exceeds the critical value (Figure 5b, results in blue), potentially causing fault reactivation and leakage. In general, a low frequency of model updates may produce excessive extraction volumes for under-estimated initial hydraulic properties, whereas for over-estimated initial hydraulic properties, a violation of pressure buildup constraints can occur affecting the robustness and safety of the GCS operation. The adaptive management strategy can reduce the risk of failure due to the uncertainties in the reservoir properties, and especially at early times frequent updates of the model are needed to increase the safety and the confidence of the GCS operation over long injection periods. However, safety factors and the associated uncertainties must be included when determining the optimization constraints (e.g., Harp et al., 2017).

Although the 10-year frequency for the model update is an extreme case as generally one would not wait 10 years for incorporating new monitoring data for model calibration, the results point to the importance of conducting a pressure management optimization with adequately calibrated prediction models based on frequent model updates, in particular early in the project. At later project stages, since more data have been collected and used to estimate the reservoir properties during the calibration step, the algorithm calculates more reliable extraction rates for controlling the pressure in the reservoir system.

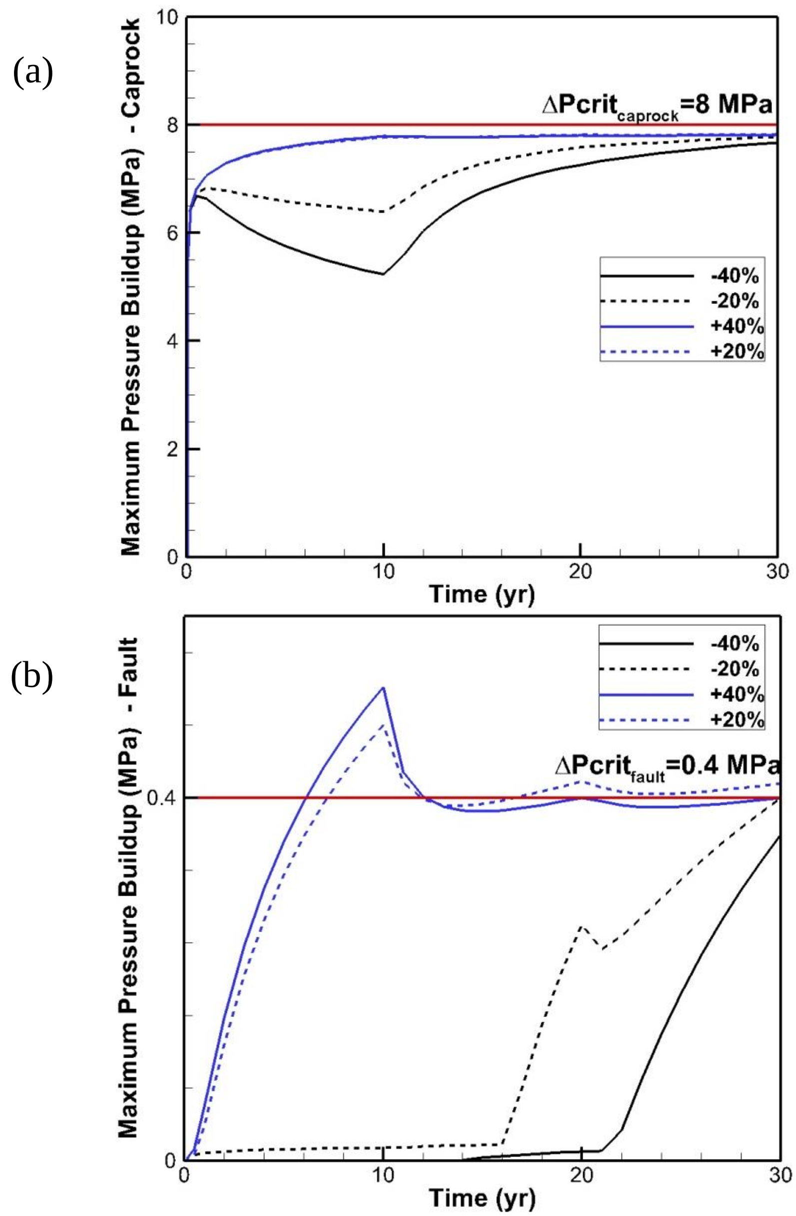

Figure 5. Maximum pressure buildup evolution registered from the observation points in response to applied optimal extraction rates, produced by a scenario with low frequency of updates (Δt= 10 years): (a) at the caprock, and (b) along the fault.

4.2 Influence of model update frequency at early times

Concerns about inadequate optimization in both directions, either excessive extraction rates (when properties are under-estimated) or potential pressure constraint violation (when properties are over-estimated) can be eliminated if one conducts much more frequent model updates, especially at early times. For example, we demonstrate below that for cases with under-estimated properties, frequent model updates at early times are highly beneficial to prevent the excessive extractions. Considering the scenario with hydraulic properties under-estimated by 20%, the pressure at the injection well reaches the critical pressure buildup for caprock fracturing within 50 days (without pressure management) and very high extraction rates are estimated with model updates conducted infrequently (say every three or every ten years). In contrast, if model updates are applied using daily pressure data during this time interval, the calculated optimal extraction rates will be very close to those for the true model even if the initial reservoir properties are off. Figure 6 shows that the root-mean-square error (RMSE) between predicted and observed pressure significantly drops (by ~four orders of magnitude) within a month or so (after four updates), which means that the calibrated hydraulic properties are similar to the true values. However, note that for more complex reservoir systems, depending on the number and type of the observations, the convergence of the model results to the observations may take much longer.

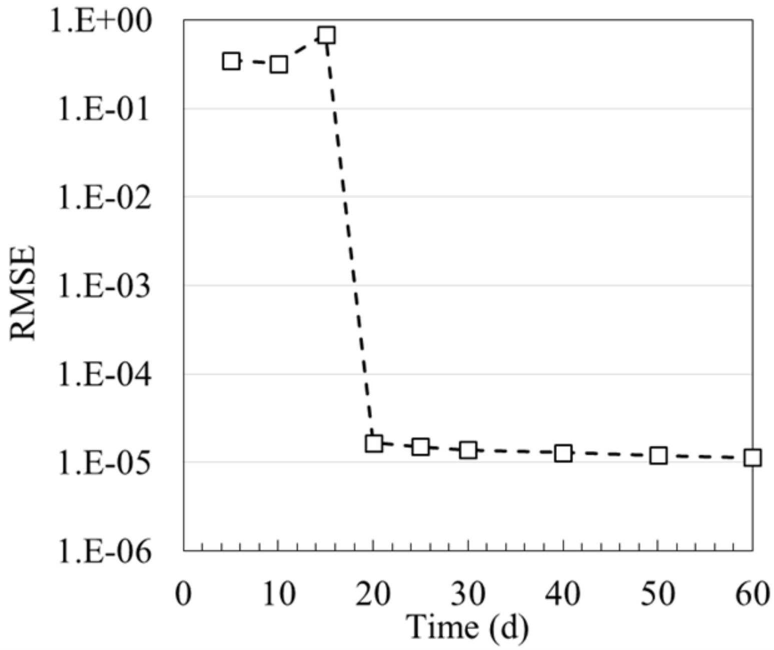

Figure 6. Scenario -20%: changes in the root-mean-square error (RMSE) between model predicted heads and observed heads for high frequency updates between time =0-60 days.

Thus, inadequate optimization can be avoided if more updates of the reservoir properties are included during the early stages of injection. Figure 7 illustrates that the optimized extraction rates computed for scenario -20% are close to the true optimal extraction rates of the reference case when we include model updates with monitoring data at a frequency of as low as 3 days within the early injection period. In contrast, when no initial updates are applied at earlier times (i.e., Δt is fixed and equal to 3 years), the extraction rate is strongly over-estimated during the first three years (solid black line), because the initial hydraulic properties of the injection formations are under-estimated and the model wrongly projects strong pressure buildup at the injection well.

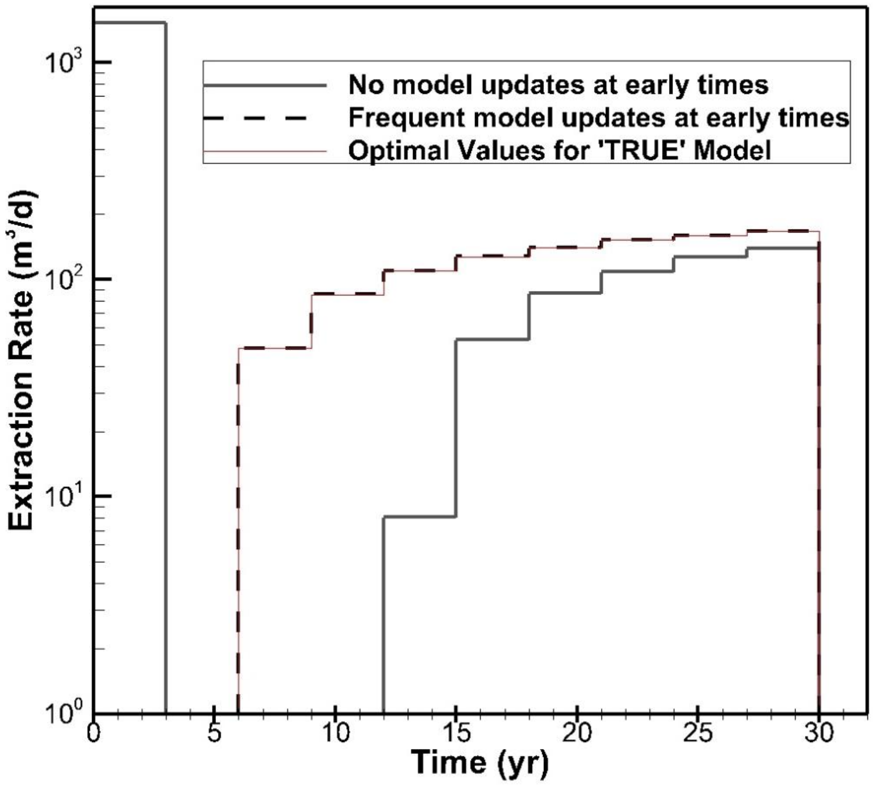

Figure 7. Calculated extraction rates based on the scenario with initial hydraulic parameters deviated by -20% are compared with the actual optimal rates for the 'true' model. 'no model updates at early times' (solid black line) corresponds to a fixed model update frequency of three years, and 'frequent model updates at early times' (dashed black) corresponds to variable frequencies of model updates (changing from three days at very early times to three years at late times).

With more initial updates, profiles of the pressure buildup (Figure 8) oscillate near the critical value due to step-wise changes in the operational extraction rates, but they never exceed the critical pressure buildups of the caprock or the fault, keeping the maximum pressure under control. As expected, the impact of the high extraction rates during the first three years in the model without frequent updates at early times is manifested on the pressure profiles. This model presents lower pressure buildups near the fault and at the injection well in comparison to the model with more frequent updates at early times. As mentioned above, the model with no updates at early times (solid line) over-estimates the extraction rate for the first period when hydraulic properties have not been yet updated. This strongly decreases the pressure buildup and does not require new extraction until time=12 years when pressure buildup at the fault approaches the maximum pressure allowed. In contrast, the model with more frequent updates at early times requires pumping, correctly, at a much earlier time (6 years). For the scenarios investigated here with initially under-estimated hydraulic conductivity values and less frequent updates at early times, our results show that the critical pressure buildup along the fault appears as the most stringent constraint, because the maximum pressure changes along the caprock, near the injection well, never comes too close to the critical pressure buildup value.

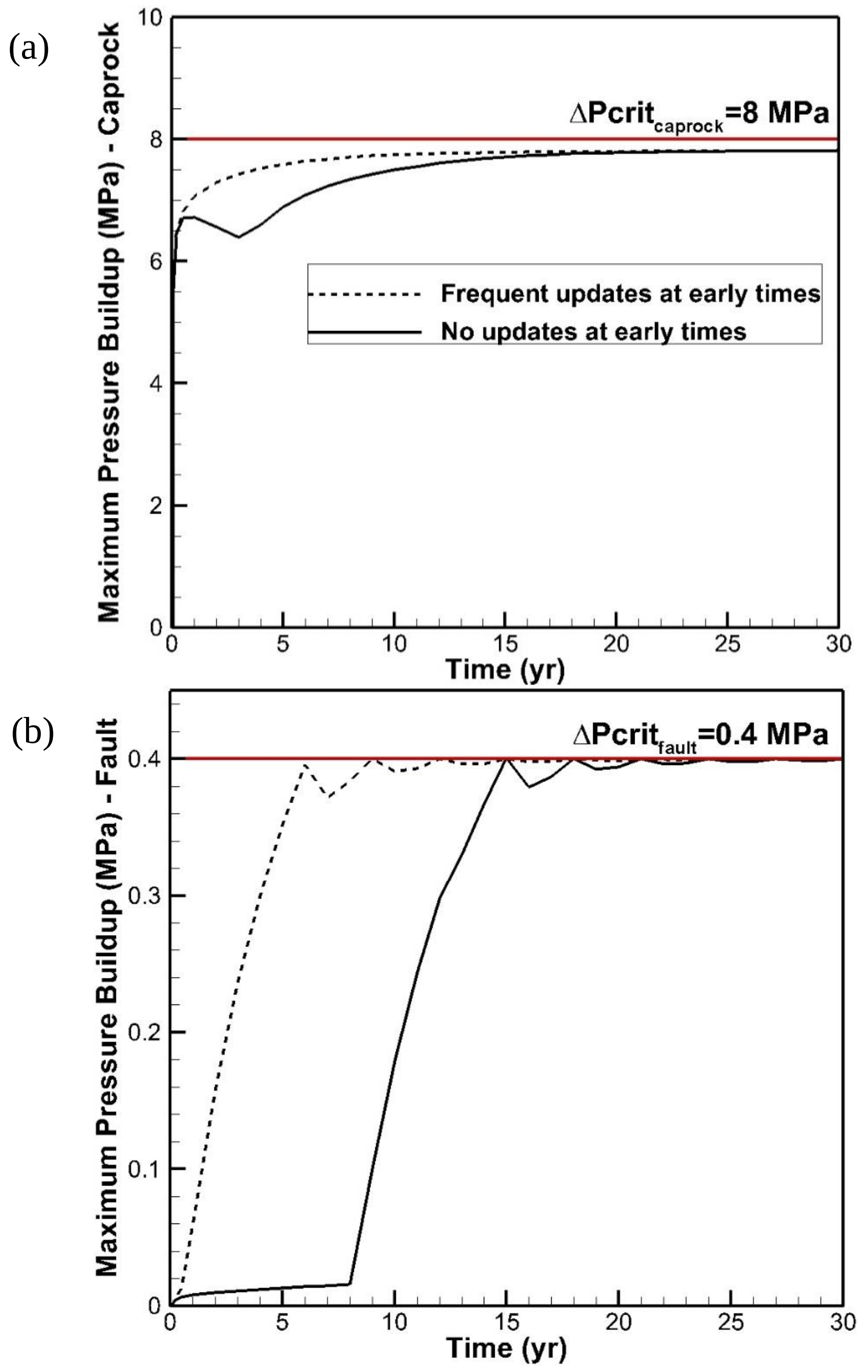

Figure 8. Maximum pressure changes ‘observed’ based on the ‘true’ model for the scenario with initial hydraulic parameters deviated by -20%. ‘no model updates at early times’ (solid black line) corresponds to a fixed model update frequency of three years, and ‘frequent updates at early times’ (dashed black) corresponds to variable frequencies of model updates (changing from three days at very early times to three years at late times): (a) Pressure buildup at the injection well, and (b) Pressure buildup along the fault.

4.3 Computational cost of the adaptive management approach

As already pointed out in Cihan et al. (2015), the number of forward calls required by the CDE algorithm used in Stage 1 and Stage 3 of the approach is high. For the scenarios applied in this study (Table 2), the maximum number of calls of the forward model for one observation time is 1,010 for the optimization (Stage 1) and 3,020 for the calibration (Stage 3), corresponding to a CPU time (or process time) of 45 minutes and 11 minutes, respectively. Note that simulations were conducted in a regular desktop PC applying parallelization. These CPU times for both stages are very affordable since we employ a semi-analytical model (Section 2.1) and obviously higher CPU times are expected if a reservoir simulator is employed. However, the adaptive management approach can easily be parallelized to work in a high performance computing cluster. We also would like to highlight that simulations related to early observations, and consequently related to better and safer results, are tied to short time of simulations (less than 15 days, Figure 8). Therefore, CPU times of the forward simulations of the reservoir simulator should be much lower (order of magnitudes) than for later stages of the injection.

5 Conclusions

Industrial scale injection of CO_2 into the subsurface can cause reservoir pressure increases that can be properly controlled via pressure management schemes such as brine extraction. Such control is important as excessive pressure buildup in a reservoir may result in groundwater contamination stemming from leakage through conductive pathways, such as improperly plugged abandoned wells or distant faults, or may trigger fault reactivation and possibly seal breaching. Knowledge of the subsurface properties is always incomplete, especially during the planning stages of CO_2 projects because of limited site characterization data and related uncertainties. Thus, during the operation of a given project, the subsurface system behavior needs to be monitored continuously, and the models and their predictions need to be frequently updated to effectively and safely control reservoir pressure.

In this study, we developed and applied an automated adaptive pressure management algorithm to understand primarily the effects of initial site characterization and frequency of model updates (calibration) and optimization calculations on the accuracy and the success of managing a subsurface reservoir system. Adaptive optimized management uses advanced automated optimization algorithms and suitable process models. Adaptive management integrates monitoring, forward modeling, inverse modeling and optimization in an iterative way. The hypothetical scenario considered here assumes CO_2 injection into a deep aquifer-aquitard (sandstone-shale) sequence, where pressure buildup from injection increases the risk of caprock failure and fault activation. We designed and optimized a pressure management strategy involving a passive relief well and an active brine extraction well to reduce pressure increases to avoid caprock damage near the injection well and decrease the risk of activating a nearby fault.

Our results show that that the success of adaptive pressure management depends strongly on the frequency rate of model updates and calibration, particularly at early times. Less frequent optimization + monitoring/testing + calibration cycles may lead to pressure buildups that exceed constraints at initial times potentially resulting in excessively high extraction rates. These conditions can be avoided or eliminated if optimization + monitoring/testing + calibration calculations are conducted with greater frequency, especially during the early injection period. The high extraction rates that the optimization algorithm finds initially for under-estimated hydraulic properties can be decreased if more model updates are conducted at the onset of injection. Similarly, early model improvement for cases with initial over-estimation of d hydraulic properties avoids the risk of under-estimating the extraction rates during the first injection years, which could result in a violation of the pressure constraints imposed for the optimization model.

We demonstrated the effectiveness of adaptive pressure management for a simple case of a reservoir system with a limited set of monitoring data from three observation wells. This framework could easily be expanded to include diverse data sets with observations made at other locations and/or over large areas comprising different physical processes such as salinity, temperature, geophysical or satellite deformation, etc. We conclude that adaptive management constitutes an effective tool to manage subsurface pressure and plume control in application to geological CO_2 storage which could be extended to other fields where injection of fluid takes place (e.g., geothermal reservoirs).

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FIGURES

Figure 1. Schematic showing the pressure management strategy in this study to reduce risk of caprock failure and risk of fault reactivation. The schematic shows the five top aquitards as well as the five top aquifers of Table 1 (from 22 to 18). Injection of CO_2 occurs into two reservoir layers (aquifers 22 and 21 in Table 1). Brines are extracted from two wells, one of them "actively" pumping to the surface, the other "passively" moving brines into deeper layers. The back of the schematic figure shows a hypothetical critically stressed fault, for which a maximum allowable pressure change has been defined. Another pressure limit is defined to avoid caprock damage.

Figure 2. Profiles of maximum pressure buildup (in MPa) (a) at the caprock and (b) at the fault. (Note that Cihan et al.'s computer program (2011) produces the results in terms of head in meters, and to convert the head buildup to pressure buildup, we used a uniform brine density of 1126.026 kg/m^3.)

Figure 3. Pressure buildup contours (in MPa) at time=30 years with (a) only passive extraction and (b) passive and active extraction (updates every 3 years) for the +20% case in Layer 22.

Figure 4. Summary of the adaptive optimization results: Variation of the estimated brine extraction ratio as a function of initial deviations from reservoir properties and model update frequency (Δt).

Figure 5. Maximum pressure buildup evolution registered from the observation points in response to applied optimal extraction rates, produced by a scenario with low frequency of updates (Δt= 10 years): (a) at the caprock, and (b) along the fault.

Figure 6. Scenario -20%: changes in the root-mean-square error (RMSE) between model predicted heads and observed heads for high frequency updates between time =0-60 days.

Figure 7. Calculated extraction rates based on the scenario with initial hydraulic parameters deviated by -20% are compared with the actual optimal rates for the ‘true’ model. ‘no model updates at early times’ (solid black line) corresponds to a fixed model update frequency of 3 years, and ‘frequent model updates at early times’ (dashed black) corresponds to variable frequencies of model updates (changing from 3 days at very early times to 3 years at late times).

Figure 8. Maximum pressure changes ‘observed’ based on the ‘true’ model for the scenario with initial hydraulic parameters deviated by -20%. ‘no model updates at early times’ (solid black line) corresponds to a fixed model update frequency of 3 years, and ‘frequent updates at early times’ (dashed black) corresponds to variable frequencies of model updates (changing from 3 days at very early times to 3 years at late times): (a) Pressure buildup at the injection well, and (b) Pressure buildup along the fault.

TABLES

Table 1. Reference (‘true’) hydraulic property values of reservoir layers containing aquifers alternating with aquitards. The bottom layer is an aquifer, and the top layer is an aquitard.

Table 2. Scenarios considered for the adaptive management framework