

Sensitivity of injection costs to input petrophysical parameters in numerical geologic carbon sequestration models



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ABSTRACT

Numerical simulations are widely used in feasibility studies for geologic carbon sequestration. Accurate estimates of petrophysical parameters are needed as inputs for these simulations. However, relatively few experimental values are available for CO₂–brine systems. Hence, a sensitivity analysis was performed using the STOMP numerical code for supercritical CO₂ injected into a model confined deep saline aquifer. The intrinsic permeability, porosity, pore compressibility, and capillary pressure-saturation/relative permeability parameters (residual liquid saturation, residual gas saturation, and van Genuchten α and m values) were varied independently. Their influence on CO₂ injection rates and costs were determined and the parameters were ranked based on normalized coefficients of variation. The simulations resulted in differences of up to tens of millions of dollars over the life of the project (i.e., the time taken to inject 10.8 million metric tons of CO₂). The two most influential parameters were the intrinsic permeability and the van Genuchten m value. Two other parameters, the residual gas saturation and the residual liquid saturation, ranked above the porosity. These results highlight the need for accurate estimates of capillary pressure-saturation/relative permeability parameters for geologic carbon sequestration simulations in addition to measurements of porosity and intrinsic permeability.

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1. Introduction

Anthropogenic levels of atmospheric greenhouse gases, particularly carbon dioxide (CO₂), have increased rapidly over the last several decades and coincide with rising temperatures globally. CO₂ concentrations in the atmosphere have risen from around 280 ppm to over 380 ppm in the last 250 years (Sundquist et al., 2008), and are currently >400 ppm (NOAA, 2013). Concerns over global warming have resulted in the need to evaluate alternative methods for dealing with CO₂ emissions. One possible alternative is to capture CO₂ before it is released into the atmosphere by large point sources such as fossil fuel power plants and cement operations. The technology for carbon capture and storage already exists and is currently implemented by the oil and natural gas industries for enhanced oil and natural gas recovery, as well as for temporary storage of natural gas (Solomon et al., 2008; Pacala and Socolow, 2004).

There are several options for storing captured CO₂ including mineralization in the form of stable carbonates, deep ocean sequestration, and sequestration in geologic formations at depth. Of these,

geologic carbon storage (GCS) is considered to be the most viable option (Yang et al., 2010; Celia and Nordbotten, 2009). Deep saline aquifers seem to be the most attractive targets for geologic carbon sequestration since they are normally unused due to high salinity, typically have high storage capacity, and are widely available (Yang et al., 2010; Pruess et al., 2003).

Numerical models are widely used for site specific investigations of geologic carbon sequestration and require a basic understanding of the available reservoirs and their petrophysical properties. Numerical simulations of CO₂ storage in geologic media span a wide range of approaches and foci (Poienot et al., 2012; Zhang and Agarwal, 2012; King et al., 2011; Birkholzer et al., 2009). Schnaar and Digiulio (2009) summarized the main processes considered in these models: multiphase flow and heat transport, reactive transport, and geochemical modeling. Multiphase flow models focus on the phase transition behavior of CO₂, buoyancy contrasts between CO₂ and brine, solubility of CO₂ in brine, leakage through abandoned wells or faults, precipitation of salt in brine, and three-phase relative permeability relationships. Heat transport is an important process in CO₂ sequestration modeling because many transport mechanisms are temperature dependent, relating mainly to cooling due to decompression of supercritical CO₂ (Gupta, 2008; Doughty, 2010; Han et al., 2011; Heath et al., 2012). Reactive transport models can simulate mineral dissolution and precipitation

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and their associated changes to petrophysical parameters as well as aquifer acidification. Modeling of geochemical processes can provide insight into aquifer and caprock pressure buildup and possible fault reactivation, as well as changes in petrophysical parameters such as porosity and intrinsic permeability.

Site-specific numerical simulations have been conducted to assess the storage capabilities for various sites and regions (e.g., Bowersox et al., 2011; Eiken et al., 2011; Frailey et al., 2011; Doughty, 2010; Frailey and Finley, 2010; Gupta, 2008; Kongsjorden et al., 1998). Injection of CO₂ on site and the monitoring of its migration have provided additional information for fine-tuning numerical simulations of subsurface CO₂ sequestration (Doughty et al., 2008; Sakurai et al., 2005). Not all GCS simulation studies are site-specific, and a number of published studies have used similar generic parameters combined with a simple geologic model (e.g., Burton et al., 2009; Esposito and Benson, 2010; Han et al., 2011; Mathias et al., 2011, 2013; Nordbotten et al., 2005; Nordbotten and Celia, 2006). Simulations of geochemical reactions, multiphase flow, and heat transport in model saline aquifers using have been run by Pruess et al. (2003) to determine the amounts of CO₂ that can be stored given certain conditions.

Some researchers have looked at the sensitivity of numerical multiphase flow models to variations in selected petrophysical parameters due to heterogeneity when modeling geologic storage of CO₂ (Han et al., 2011; Doughty, 2010; Sifuentes et al., 2009; Juanes et al., 2006; Mo and Akervoll, 2005). Variations in the costs of carbon capture, transport, and storage have also been investigated (Heath et al., 2012; Middleton et al., 2012; Poiencot et al., 2012; Cinar et al., 2008; McCoy and Rubin, 2009). However, to the authors' knowledge no other study has systematically varied the full suite of petrophysical parameters required for numerical modeling of geologic CO₂ sequestration and used the outputs to evaluate the relative impact on injection costs. This analysis is important because it will help researchers identify the most influential petrophysical parameters which must be most accurately measured.

This paper focuses on modeling geologic CO₂ sequestration in a model deep confined saline aquifer using the STOMP numerical code. The simplified modeling domain employed eliminates many of the complexities encountered in the field so that we can focus on individual parameter effects. A sensitivity analysis was performed to examine the relative influence of input petrophysical parameters on CO₂ storage prediction. The parameters investigated were intrinsic permeability, porosity, pore compressibility, the van Genuchten α parameter, the van Genuchten m parameter, the van Genuchten residual liquid saturation, the Corey residual liquid saturation, and the Corey residual gas saturation. The simulation outputs were analyzed to quantify the impact of petrophysical parameters and their measurement accuracy on injection costs.

2. Materials and methods

Numerical simulations were carried out using the Subsurface Transport over Multiple Phases (STOMP) code (White and Oostrom, 2006). This code was developed by the Hydrology group at Pacific Northwest National Laboratory (PNNL). STOMP simulates subsurface flow and transport processes in variably-saturated porous media by solving the governing equations with the integral volume finite difference method and Newton–Raphson iteration (White and Oostrom, 2006). STOMP-CO₂ is specifically designed for modeling the injection of CO₂ into target reservoir formations. It operates under the main assumptions that isothermal conditions exist, that there is no oil phase or dissolved oil present, and that local thermodynamic equilibrium exists.

The main petrophysical inputs required in STOMP-CO₂ are the porosity, the intrinsic permeability, the pore compressibility, and

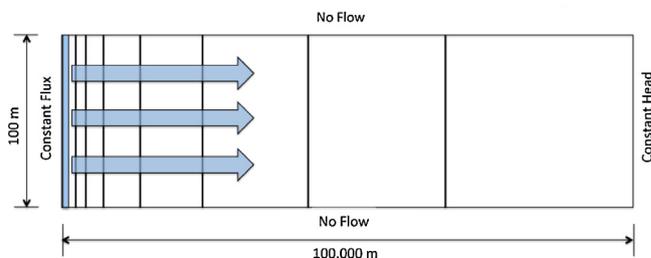


Fig. 1. Schematic representation of the model domain, which is based on the simulations reported by Pruess et al. (2002). One hundred grid cells were used with spacing increasing exponentially with distance from the injection well on the left. The arrows indicate injected CO₂.

the van Genuchten (1980) and Corey (1954) parameters describing the capillary pressure versus saturation and relative gas and liquid permeability functions. The van Genuchten (1980) capillary pressure-saturation function is implemented in STOMP-CO₂ as follows (White and Oostrom, 2006):

$$\bar{S}_{lvG} = \left[1 + (\alpha h_{gl})^{1/(1-m)} \right]^m; \quad \bar{S}_{lvG} = \frac{S_l - S_{lrVG}}{1 - S_{lrVG}} \quad (1)$$

where \bar{S}_{lvG} is the effective van Genuchten liquid saturation, α is a fitting parameter related to initial gas entry, h_{gl} is the gas-aqueous capillary head (m), m is a fitting parameter related to the pore-size distribution, S_l is the liquid saturation, and S_{lrVG} is the van Genuchten residual liquid saturation. In STOMP-CO₂ the aqueous relative permeability relation, K_{rl} , is predicted based on the van Genuchten (1980) capillary pressure-saturation function:

$$K_{rl} = \bar{S}_{lvG}^{0.5} \left\{ 1 - \left[1 - \bar{S}_{lvG}^{-(1/m)} \right]^m \right\}^2 \quad (2)$$

while the gas relative permeability relation, K_{rg} , is predicted using the Corey (1954) formulation, i.e.

$$K_{rg} = (1 - \hat{s})^2 (1 - \hat{s}^2); \quad \hat{s} = \frac{S_l - S_{lrC}}{1 - S_{lrC} - S_{grC}} \quad (3)$$

where \hat{s} is the Corey effective saturation, S_{lrC} is the Corey residual liquid saturation, and S_{grC} is the Corey residual gas saturation (White and Oostrom, 2006).

The residual gas saturation represents the CO₂ that becomes trapped in pores and cannot be displaced by the liquid phase following injection. Similarly, the residual liquid saturation represents the liquid that is trapped in pores and cannot be displaced by the injected gas phase. There are two distinct versions of this parameter defined in Eqs. (1) and (3). This is because the van Genuchten and Corey parameters are typically determined by separate experimental approaches: quasi-static capillary pressure-saturation versus dynamic permeability/core flood tests. These two methods can yield different residual saturation estimates. Thus, the van Genuchten and Corey residual liquid saturations are treated as independent parameters in STOMP-CO₂.

A model injection scenario was created in STOMP-CO₂ following Pruess et al. (2002) for simulating radial flow of supercritical CO₂ from an injection well into a deep saline aquifer (Fig. 1 and Table 1). A 100 m thick, isotropic and homogeneous aquifer of 100 km radial extent was simulated with supercritical CO₂ injected in the center of the infinite-acting domain at various rates for 10,000 days (approximately 27 years). The multiple phases considered in this model were CO₂ and brine (15 wt% salinity). The default aquifer temperature and pressure were selected to maintain CO₂ in a supercritical state (Table 1). The initial pressure of 120 MPa corresponds to a depth at of \sim 1200 m. There was a constant flux boundary on the left hand side at the injection well, a constant head boundary on the right hand side, with no-flow boundaries at the top and bottom

Table 1
Default parameter values for the base scenario and tested value ranges for the sensitivity analysis using STOMP-CO₂.

Parameter	Default value	Range
Intrinsic permeability (m ²)	1.0 × 10 ⁻¹³	1.0 × 10 ⁻¹² –5.0 × 10 ⁻¹⁴
Porosity (m ³ m ⁻³)	0.12	0.04–0.24
Pore compressibility (Pa ⁻¹)	4.5 × 10 ⁻¹⁰	2.5 × 10 ⁻¹⁰ –7.5 × 10 ⁻¹⁰
van Genuchten <i>m</i> value	0.457	0.426–0.772
van Genuchten <i>α</i> value (m ⁻¹)	0.5	0.5–3.0
Corey residual gas saturation	0.05	0.05–0.30
Corey residual liquid saturation (m ³ m ⁻³)	0.3	0.15–0.40
van Genuchten residual liquid saturation (m ³ m ⁻³)	0.0	0.0–0.3
CO ₂ injection rate (kg/s)	12.5	0.17–120
Initial aquifer temperature (°C)	45	– ^a
Initial aquifer pressure (Pa)	1.2 × 10 ⁷	– ^a
Initial aquifer salinity (wt% NaCl)	15	– ^a

^a These parameters were held constant in all the simulations.

of the model aquifer (Fig. 1). One hundred grid cells were employed with spacing increasing exponentially with distance from the injection well. Gravity and inertial effects were neglected and flow was assumed to be exclusively one-dimensional. It was also assumed that the reservoir rock will not fail at the buildup pressures achieved in the simulations.

The default input values for a suite of commonly-used parameters (referred to as the base scenario) are listed in Table 1 along with the ranges of values included in the sensitivity analysis. The petrophysical properties for the base scenario are similar to those expected for an unfractured (or sparsely fractured) sandstone aquifer. Each petrophysical parameter was varied incrementally over a reasonable range, which included the default value, while holding all of the other parameters constant. This “one-at-a-time” approach, in which a suite of parameters is varied independently, is the standard method for conducting a sensitivity analysis in hydrogeology (Anderson and Woessner, 2002).

The range of variation studied (Table 1) depended upon the specific parameter under investigation. We attempted to encompass the majority of values used as inputs in other published modeling studies. The range of intrinsic permeability values investigated matched the limits (1 millidarcy to 1 Darcy) for a United States Geological Survey (USGS) Class II storage formation, which is expected to have the highest storage efficiency for residual trapping (Brennan et al., 2010). The use of intrinsic permeability values $\leq 5 \times 10^{-14}$ m², however, resulted in the buildup of high hydrostatic pressures (> 100 MPa) close to the injection well. Such pressures could be expected to result in hydraulic fracturing. Since this study was focused on unfractured conditions, these low intrinsic permeability simulations were not included in the final results. The range of porosity values tested was based on the simulation studies conducted by Doughty (2010) and Han et al. (2011). The van Genuchten *m* values came from the study by Cropper et al. (2011) and represent both different porous media and measurement methods. The other parameters were simply varied stepwise over reasonable ranges suggested by the literature (Gragg, 2012).

Numerical simulations were run for each parameter under scrutiny, corresponding to eight different CO₂ injection rates for most parameters (i.e., 3.13, 6.25, 12.5, 18.75, 21.88, 25, 50, and 100 kg/s). Due to large variations in the simulated pressure distributions associated with changing the intrinsic permeability, additional injection rates were employed for this parameter (i.e., 0.10, 0.20, 0.41, 0.82, 1.63, and 150 kg/s). For each parameter, a plot of injection rate versus mean gas pressure within the aquifer was created. The mean aquifer pressure was calculated by summing the gas pressure values for each grid cell after 10,000 days and then dividing by the total number of grid cells. Using linear regression, a relationship between the injection rate and the mean gas pressure was then established. From this relationship an injection rate associated with the mean gas pressure corresponding to

the base scenario (i.e., the default parameter values in Table 1) could be calculated for each parameter (hereafter, referred to as the corresponding injection rate).

The derived corresponding injection rates were then used to calculate the cost per metric ton of injected CO₂ for each parameter. The capital cost for a single well was calculated from Ogden (2002) such that:

$$\text{Capital (\$/well)} = \$1.25 \text{ million} + \$1.56 \text{ million/km of depth} \quad (4)$$

Operation and maintenance for the well were assumed to be 4% of capital with an annual capital charge rate of 15% of the total capital, resulting in a yearly cost of \$714,330 in 2001 USD (Heath et al., 2012). Assuming a yearly inflation rate of 1.023%, the yearly cost of operating the injection well would be \$917,341 in 2012 USD. This value was then used as a rough estimate of the cost to operate the injection per year for a single well when calculating the cost as \$ per metric ton of CO₂ injected.

In order to compare the cost effects due to varying the different petrophysical properties, normalization was done to account for the differences in ranges and to eliminate units. For example, comparing the costs due to varying intrinsic permeability with the costs associated with variations in the van Genuchten *m* value is unreasonable since these parameters have different units and their ranges of variation were vastly different. Therefore, a normalized coefficient of variation, CV_n , was calculated for each parameter using the following expressions:

$$CV_p = \left(\frac{\sigma_p}{\bar{x}_p} \right) \times 100\% \quad (5)$$

$$CV_\$ = \left(\frac{\sigma_\$}{\bar{x}_\$} \right) \times 100\% \quad (6)$$

$$CV_n = \left(\frac{CV_\$}{CV_p} \right) \times 100\% \quad (7)$$

where CV_p is the coefficient of variation for the parameter values, σ_p is the standard deviation for the parameter values, \bar{x}_p is the mean of the parameter values, $CV_\$$ is the coefficient of variation of the cost per ton, $\sigma_\$$ is the standard deviation of the cost per ton, and $\bar{x}_\$$ is the mean cost per ton. The CV_n statistic provides a normalized measure of the fluctuation in injection costs (i.e., the price per ton of CO₂) produced by varying a particular parameter. The larger the value of CV_n , the more sensitive the injection costs are to changes in a given petrophysical property.

3. Results

The variations in the different input petrophysical parameters are summarized as CV_p values in Table 2. The intrinsic permeability was varied over the widest range ($CV_p = 106.77\%$), while the

Table 2
Coefficients of variation for each petrophysical parameter tested.

Parameter	$CV_p(\%)$	$CV_s(\%)$	$CV_n(\%)$	Rank
Intrinsic permeability	106.77	103.75	97.17	1
van Genuchten m value	19.69	17.60	89.37	2
Corey residual gas saturation	53.45	29.23	54.69	3
Corey residual liquid saturation	34.02	9.49	27.90	4
Porosity	53.45	4.21	7.88	5
Pore compressibility	37.42	2.32	6.20	6
van Genuchten residual liquid saturation	64.81	1.36	2.09	7
van Genuchten α value	53.45	0.04	0.08	8

van Genuchten m parameter had the narrowest range of values ($CV_p = 17.60\%$). This is to be expected, because intrinsic permeability in an aquifer usually varies over several orders of magnitude, whereas the van Genuchten m value is an exponent operator that produces large changes in the capillary pressure-saturation curve with relatively little variation.

Outputs from the model simulations included the aqueous CO_2 mass fraction, the CO_2 gas saturation, and the CO_2 gas pressure expressed as functions of radial distance from the injection well and time (Figs. 2 and 3). These plots are similar to those presented by Pruess et al. (2002). The aqueous CO_2 mass fraction represents the mass of CO_2 dissolved in the aquifer brine compared to the mass of the aquifer brine. For all of the parameters investigated there was a sharp increase in the aqueous CO_2 mass fraction near the injection well (e.g., Fig. 2). The offset from the injection well represents a zone of brine dry out, where the only aqueous CO_2 dissolved was in brine trapped within very small pores. This zone was followed by a fairly level phase extending out to between 3000 and 4000 m at the 27 year time step for most of the parameters investigated. At the gas front, the aqueous CO_2 mass fraction rapidly declined and asymptotically approached zero (Fig. 2).

The gas saturations for all of the selected parameters were unity near the injection site (i.e., complete gas saturation) and declined rapidly as distance from the injection well increased (Fig. 2). Beyond

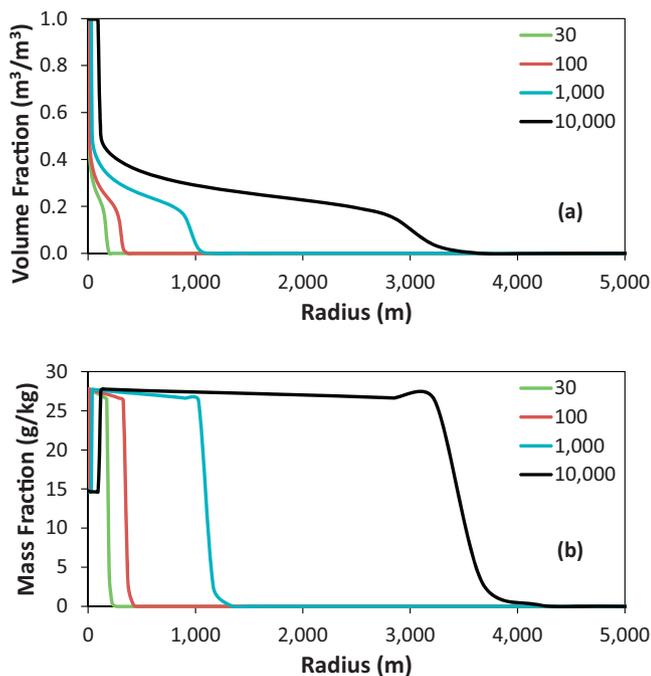


Fig. 2. Gas volume fractions (a) and aqueous CO_2 mass fractions (b) as a function of radial distance from the injection well after four simulation time steps (numbers are in days) for the base scenario (default input values). Note 10,000 days is approximately 27 years.

this point the aquifer was fully saturated with respect to brine and contained no gaseous CO_2 . Fig. 3 shows the gas pressure curves for different values of the intrinsic permeability parameter after 10,000 days at an injection rate of 12.5 kg/s. The breaks in the slopes beyond about 2500 m represent the penetration front of the gas plume.

The mean gas pressure after 10,000 days for each simulation was computed and used to compare the effects of the different petrophysical parameters on injection rates and costs (Figs. 4 and 5). As an example, Fig. 4a shows the mean gas pressure as a function of injection rate for various values of the intrinsic permeability. From the linear relationships in Figs. 4 and 5, injection rates were interpolated for each petrophysical parameter corresponding to the average aquifer pressure produced by the base scenario after 10,000 days. These interpolated injection rates were then translated into the cost in \$ per metric ton of CO_2 sequestered for each petrophysical parameter as described in Section 2. The fluctuations in cost per ton due to variations in the different input parameters are summarized as CV_s values in Table 2. The greatest variation in injection costs was produced by changing the intrinsic permeability ($CV_s = 103.75\%$), while the varying the van Genuchten α parameter had the least impact on injection costs ($CV_s = 0.04\%$).

Because the different input parameters were varied over different ranges, normalized coefficients of variation, CV_n , were computed for the injection costs to take into account these differences. These results are also summarized in Table 2. It can be seen that the normalized costs were most sensitive to variations

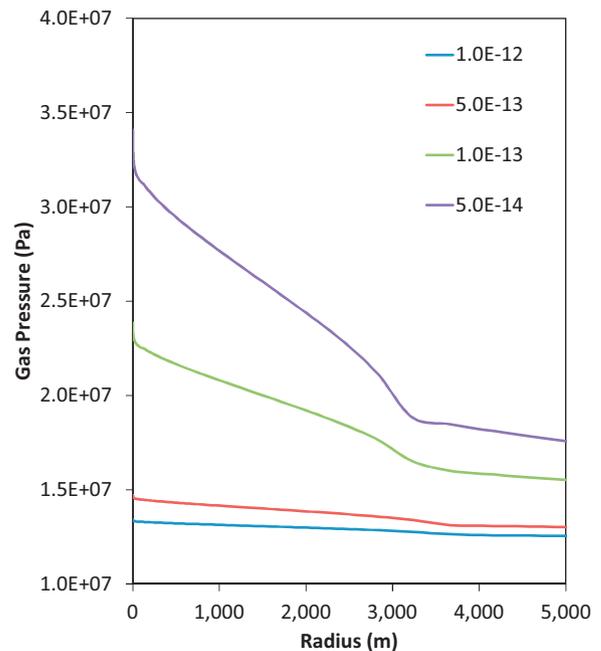


Fig. 3. Gas pressure as a function of radial distance from the injection well for various values of the intrinsic permeability (numbers are in m^2) after approximately 27 years at an injection rate of 12.5 kg/s.

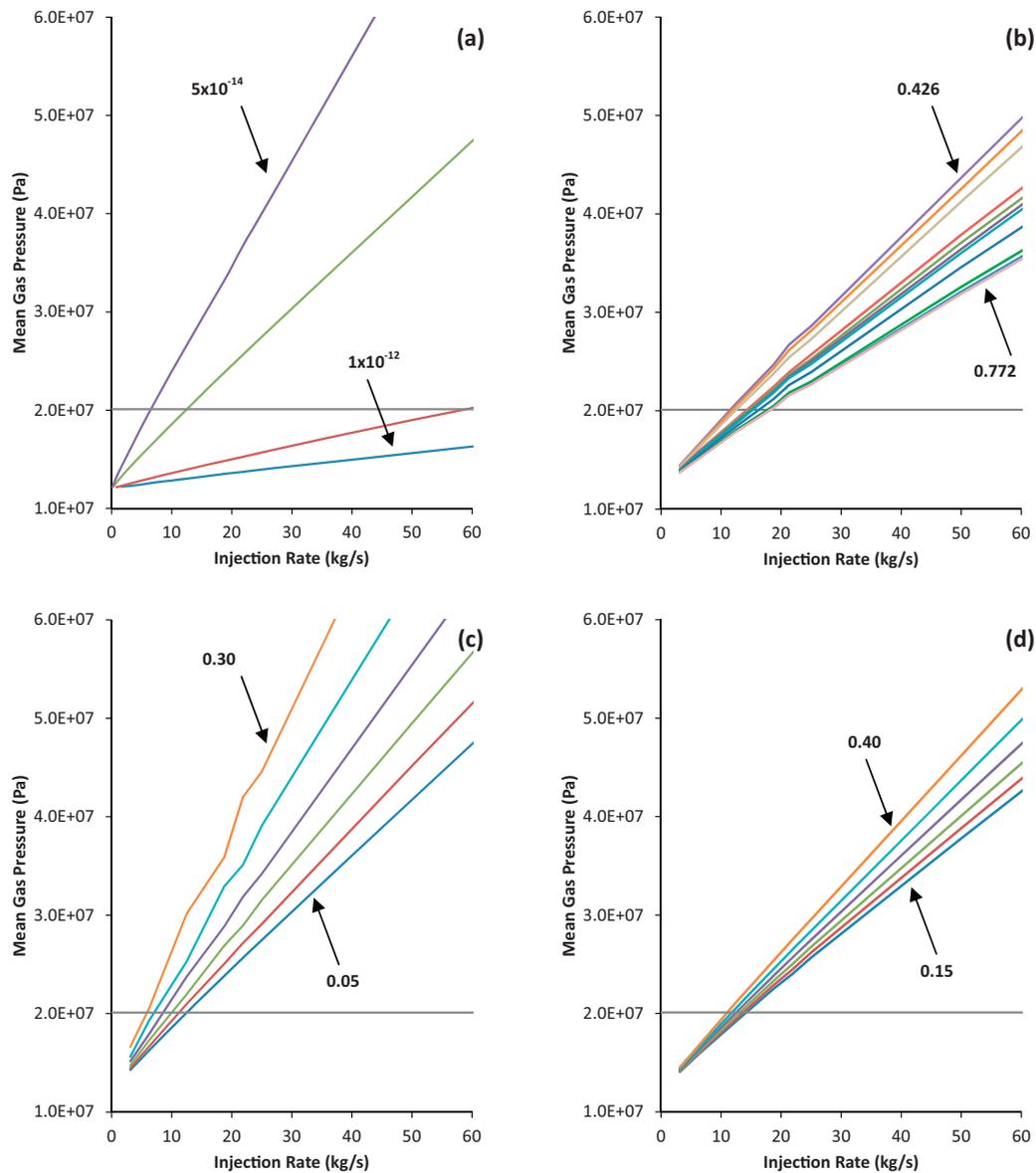


Fig. 4. Comparison of mean gas pressure as a function of injection rate for various values of (a) intrinsic permeability (b) van Genuchten m value, (c) Corey residual gas saturation, and (d) Corey residual liquid saturation. Different colored lines represent different parameter values; for clarity, only the minimum and maximum parameter values are identified. The horizontal line represents the mean gas pressure associated with the base scenario.

in the intrinsic permeability ($CV_n = 97.17\%$), and least sensitive to variations in the van Genuchten α parameter ($CV_n = 0.08\%$). It is interesting to note that the van Genuchten m exponent was the second most important input parameter in terms of normalized costs ($CV_n = 89.37\%$), despite undergoing the least amount of parameter variation in terms of CV_p (Table 2). It is also worth pointing out that variations in the total porosity, which have been widely studied in this context, have relatively little impact on normalized costs ($CV_n = 7.88\%$) when the intrinsic permeability is fixed.

4. Discussion

Intrinsic permeability was the petrophysical parameter that had the greatest impact on the calculated CO_2 injection costs (Table 2). This parameter was varied stepwise, ranging from 1.0×10^{-12} to $5.0 \times 10^{-14} \text{ m}^2$, with $1.0 \times 10^{-13} \text{ m}^2$ being the model default. These values produced a very wide range of corresponding injection rates from 0.17 kg/s for the lowest intrinsic permeability value to 119.20 kg/s for the highest intrinsic permeability value. The

calculated injection costs ranged from \$0.24 to \$168.50 per ton of injected CO_2 . Not surprisingly, the lowest intrinsic permeability value was associated with the highest cost per ton of CO_2 injected while the highest intrinsic permeability value was associated with the lowest cost per ton. The extreme fluctuations in cost demonstrate the sensitivity of the model to small shifts in the input values for intrinsic permeability.

It should be noted that the CV_p statistic for intrinsic permeability was also calculated based on the logarithms of the input values due to the commonly accepted notion that this parameter is log-normally distributed. This approach did not change the rankings in Table 2; since the calculation produced a smaller CV_p value, the CV_n statistic was even larger, further emphasizing the need for accurate estimates of the intrinsic permeability.

The van Genuchten m exponent, related to the pore size distribution, was the second most important parameter, with a CV_n of 89.37%, behind intrinsic permeability with respect to induced variations in injection costs (Table 2). Injection rates ranging from 11.56 to 19.21 kg/s were required to produce the mean aquifer pressure

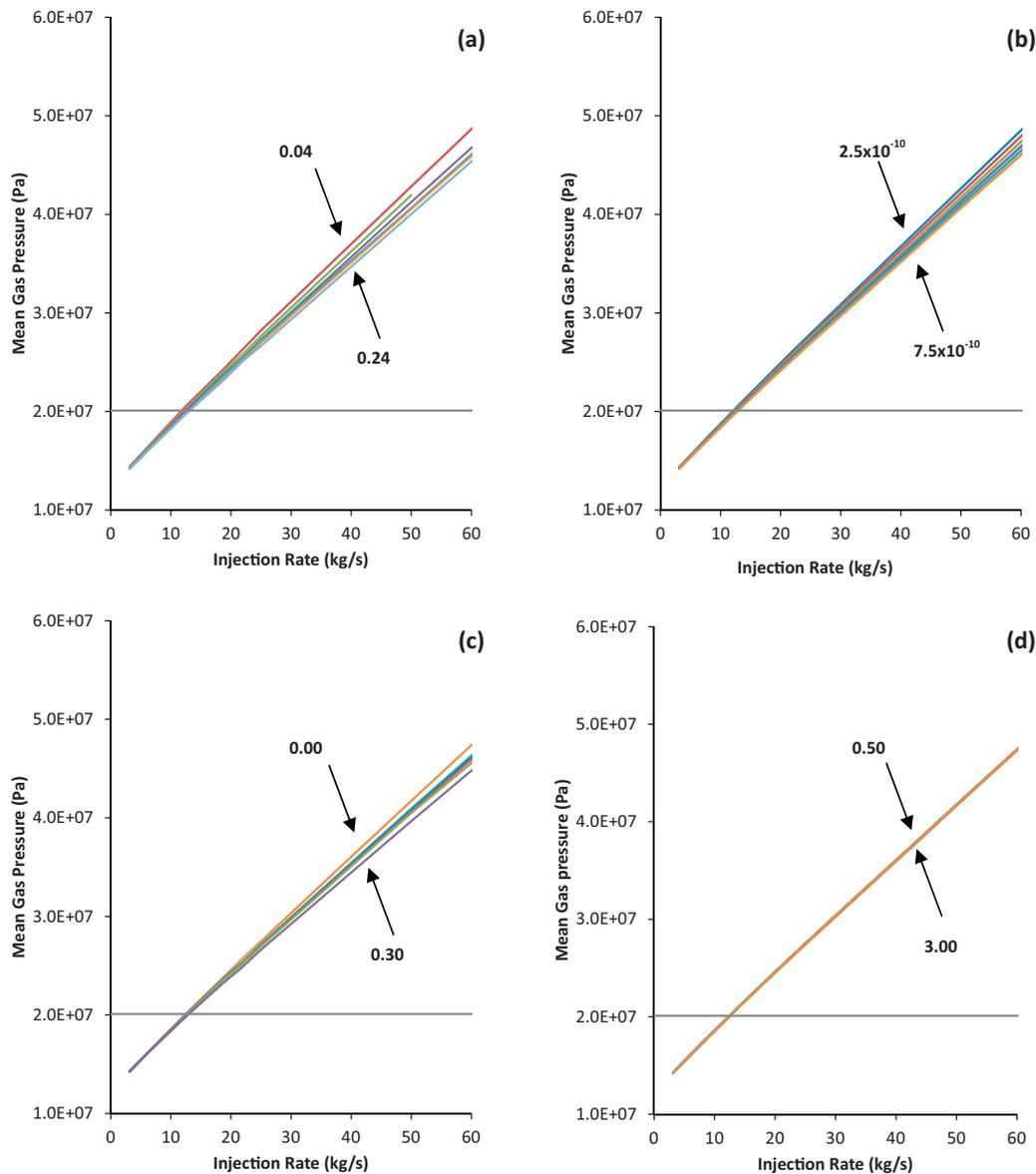


Fig. 5. Comparison of mean gas pressure as a function of injection rate for various values of (a) porosity (b) pore compressibility (c) van Genuchten residual liquid saturation and (d) van Genuchten α value. Different colored lines represent different parameter values; for clarity, only the minimum and maximum parameter values are identified. The horizontal line represents the mean gas pressure associated with the base scenario.

associated with the base scenario, with higher m values associated with higher injection rates and lower costs per ton of CO₂ injected. The resulting price per ton of CO₂ for this parameter ranged from \$1.52 to \$2.52.

The observation that m has such a large impact on injection costs should be an important stimulus for future experimental studies. Of the capillary pressure-saturation parameters, the m exponent has been shown to be the most sensitive to the estimation method employed (Cropper et al., 2011). Furthermore, only a few capillary pressure versus saturation data sets are currently available for CO₂ gas or supercritical CO₂ displacing water or brine in porous media (e.g., Chalbaud et al., 2007; Plug and Bruining, 2007). None of these appear to have been parameterized in terms of Eq. (1). As a result, a representative value of m of 0.457 is often used in modeling studies of geologic carbon sequestration (e.g., Birkholzer et al., 2009; Pruess et al., 2003). Clearly, additional experimental data are needed to provide accurate input values of m for numerical simulations.

The Corey residual gas saturation was varied stepwise by a constant value of 0.05 from 0.05, the default value, to 0.30. This resulted in a range of injection rates from 5.91 to 12.50 kg/s. The lower residual gas saturation values were associated with higher injection rates and lower costs per ton of CO₂ injected. Prices ranged from \$2.33 to \$4.93 per ton of injected CO₂. The resulting CV_n for residual gas saturation was 54.69%, representing the third highest variation among the parameters tested (Table 2). At first glance this result is somewhat surprising since CO₂ injection into a brine aquifer represents a drainage process. However, residual gas saturation appears as a parameter in the relative gas permeability function, Eq. (3), and thus influences the overall shape of the function. The simulations are quite sensitive to the shape of the K_{rg} function even during drainage.

Variations in the Corey residual liquid saturation from 0.15 to 0.40 produced a relatively narrow spread in corresponding injection rates, from 11.05 to 14.20 kg/s. The resulting variations in cost ranged from \$2.05 to \$2.63 per ton of CO₂. These results translated

into a CV_n for the Corey residual liquid saturation of 27.90%, ranking it fourth among the parameters investigated (Table 2).

The default porosity of the model formation was 0.12. This value was varied incrementally from 0.04 to 0.24 with lower porosity values requiring lower injection rates to produce a mean gas pressure equal to the base scenario. This resulted in a higher price per ton of CO_2 injected. Prices ranged from \$2.22 for the highest porosity value to \$2.46 for the lowest. The CV_n for porosity was 7.88%, ranking it fifth amongst the petrophysical parameters tested (Table 2). It is clear that the model was not as greatly influenced by shifts in the value of porosity as was originally anticipated. However, it should be noted that the model assumed there was no relationship between porosity and intrinsic permeability. In other words, a change in porosity was not reflected in the value of intrinsic permeability, despite the fact that these parameters are often positively correlated in the real world. This may explain in part the low sensitivity of the simulations to changes in porosity.

The CV_n for pore compressibility was 6.25%, the sixth highest among the parameters tested (Table 2). Pore compressibility values ranged from 2.5×10^{-10} to $7.5 \times 10^{-10} \text{ Pa}^{-1}$ and produced injection rates from 12.15 to 12.93 kg/s, respectively. The highest pore compressibility values resulted in the highest injection rates and the lowest cost per ton of CO_2 injected into the model aquifer with prices ranging from \$2.25 to \$2.40.

The two input parameters with the least impact on injection costs were the van Genuchten residual liquid saturation and the van Genuchten α value, which is related to initial gas entry pressure. The default van Genuchten residual liquid saturation was zero (Table 1). Increasing this value from 0.10 up to 0.30 by increments of 0.05 created only minor variations in the injection rate corresponding to the base scenario mean aquifer pressure. As a result, variations in costs were minimal. This is reflected in the very low CV_n value of 1.24% (Table 2). Similarly, the van Genuchten α value showed very little variation in mean gas pressure due to stepwise shifts from 0.5 to 3.0 m^{-1} . This was expressed as very small changes in the injection rate needed to maintain the same mean pressure as the base scenario. As a result, the amount of CO_2 sequestered per year varied only slightly, and the shifts in the van Genuchten α value had almost no bearing on the final cost per ton of CO_2 . As a result, the CV_n for the van Genuchten α value was only 0.08%, ranking it last among the parameters tested (Table 2).

5. Conclusions

Using a model confined saline aquifer, multiple injection simulations were run in STOMP- CO_2 with independently varied petrophysical parameters. The mean pressure in the aquifer was computed for each parameter value and injection rate. The injection rate corresponding to the mean aquifer pressure from the default scenario was then used to calculate the cost per metric ton of CO_2 injected into the model aquifer based on the economic analysis of Heath et al. (2012).

Intrinsic permeability, the van Genuchten m value, the Corey residual gas saturation, and the Corey residual liquid saturation were the most influential input parameters. While intrinsic permeability may be typically measured with acceptable accuracy, the other parameters associated with capillary pressure-saturation/relative permeability functions are rarely estimated for CO_2 -brine systems. Although porosity was not a major factor in the simulations, it may still be important for geologic materials where porosity correlates with intrinsic permeability. Porosity has the advantage of being a relatively easy parameter to reliably measure. Our results suggest the need for accurate measurements of all these parameters in order to correctly predict injection costs. Errors in measurement or imprecise estimation could result in inaccurate

cost projections on the order of a few million to tens of millions of dollars over the life of the project (the time taken to inject 10.8 million metric tons of CO_2 in this case).

Although this study is based on a homogenous, perfectly-confined, unfractured model saline aquifer, the cost estimates can provide useful reference bases for prioritizing measurements of reservoir parameters. A similar approach could also be applied to more complex systems, e.g., leaky, fractured, and/or heterogeneous aquifers, and it is possible that the ranking of influential parameters may be different for such systems. Further research is also needed to investigate the effects of possible correlations between parameters and the effect of such correlations on injection costs. Cost estimates for GCS are vital for policy and decision makers evaluating carbon capture and storage strategies. The findings of this paper should provide a useful baseline for scientists and decision makers involved in petrophysical characterization for GCS simulation.

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