ECONOMIC UNCERTAINTY IN SUBSURFACE CO_2 STORAGE: GEOLOGICAL INJECTION LIMITS AND CONSEQUENCES FOR CARBON MANAGEMENT COSTS

Peter H. Kobos, Sandia National Laboratories, (505) 845-7086, phkobos@sandia.gov
Jesse D. Roach, Sandia National Laboratories
Jason E. Heath, Sandia National Laboratories
Thomas A. Dewers, Sandia National Laboratories
Sean A. McKenna, Sandia National Laboratories
Geoff T. Klise, Sandia National Laboratories
Jim L. Krumhansl, Sandia National Laboratories
David J. Borns, Sandia National Laboratories
Karen A. Gutierrez, Sandia National Laboratories
Andrea McNemar, National Energy Technology Laboratory

Abstract

Storing large volumes of carbon dioxide (CO_2) in saline formations is a potential option to mitigate CO_2 emissions from power generating stations from entering the atmosphere. Inherent to this storage resource is substantial economic and operational uncertainty throughout the CO_2 emissions capture, transportation, injection, and storage supply chain. A critical component of the physical viability of CO_2 storage is the ability of a formation to accommodate and store vast quantities of CO_2. Much has been written on the uncertainties associated with building a CO_2 capture system and the potential storage volumes available in saline formations. However, useful storage is contingent on the ability to physically inject CO_2 into geological strata with appropriate injection rates to meet storage goals. Geological heterogeneity can dictate how quickly and sustainably any given project can inject and store CO_2 under site-specific conditions. Without suitable subsurface permeability, injecting CO_2 in a formation may not be physically and economically viable for large quantities of CO_2 involved with, for example, an 1800 MW subcritical power plant with 90% capture (more than 10 million metrics tonnes of CO_2/yr).

The purposes of this paper are to: 1) demonstrate the dependency of well injection rates and associated costs on formation permeability; and 2) determine the ranges in permeability values and other geologic parameters that would physically limit the feasibility of CO_2 injection at a storage site. We present several scenarios of CO_2 injection into varying permeability formations that are chosen as representative of the geological strata throughout the United States that are under consideration for CO_2 storage.

1. Introduction

The Water, Energy, and Carbon Sequestration simulation model (WECSsim) addresses the potential for scale-up of carbon dioxide (CO_2) capture and storage in the United States by developing several key scenarios regarding well injection rates for CO_2 storage in representative saline formations. The WECSsim model is an integrated assessment model that contains multiple interacting modules for quantifying the physical processes and economic costs of CO_2 capture, transport, and storage (CCS) in geologic formations (Fig. 1). WECSsim includes optional analysis of brine extraction from the geologic formation for dual benefits of CO_2 plume management and/or brine treatment for beneficial use above ground.

WECSsim links well injection costs to reservoir properties by incorporating extensive subsurface analysis using reservoir flow simulation and geostatistical techniques. These techniques evaluate injection flow rates as constrained by geological heterogeneity in absolute and relative permeability, porosity, and capillary pressure. Injection rates, in turn, determine the total number of wells needed to accommodate the CO_2 captured at the power plant. The total number of wells is used to calculate injection-related costs of CO_2 capture and storage. WECSsim builds upon existing geological databases and extensive supplemental geological information in an attempt to inform scenarios with the best available representation of the potential national subsurface storage resource. A primary output of the WECSsim assessment model is to calculate the variation of CCS costs for power plants across the United States.

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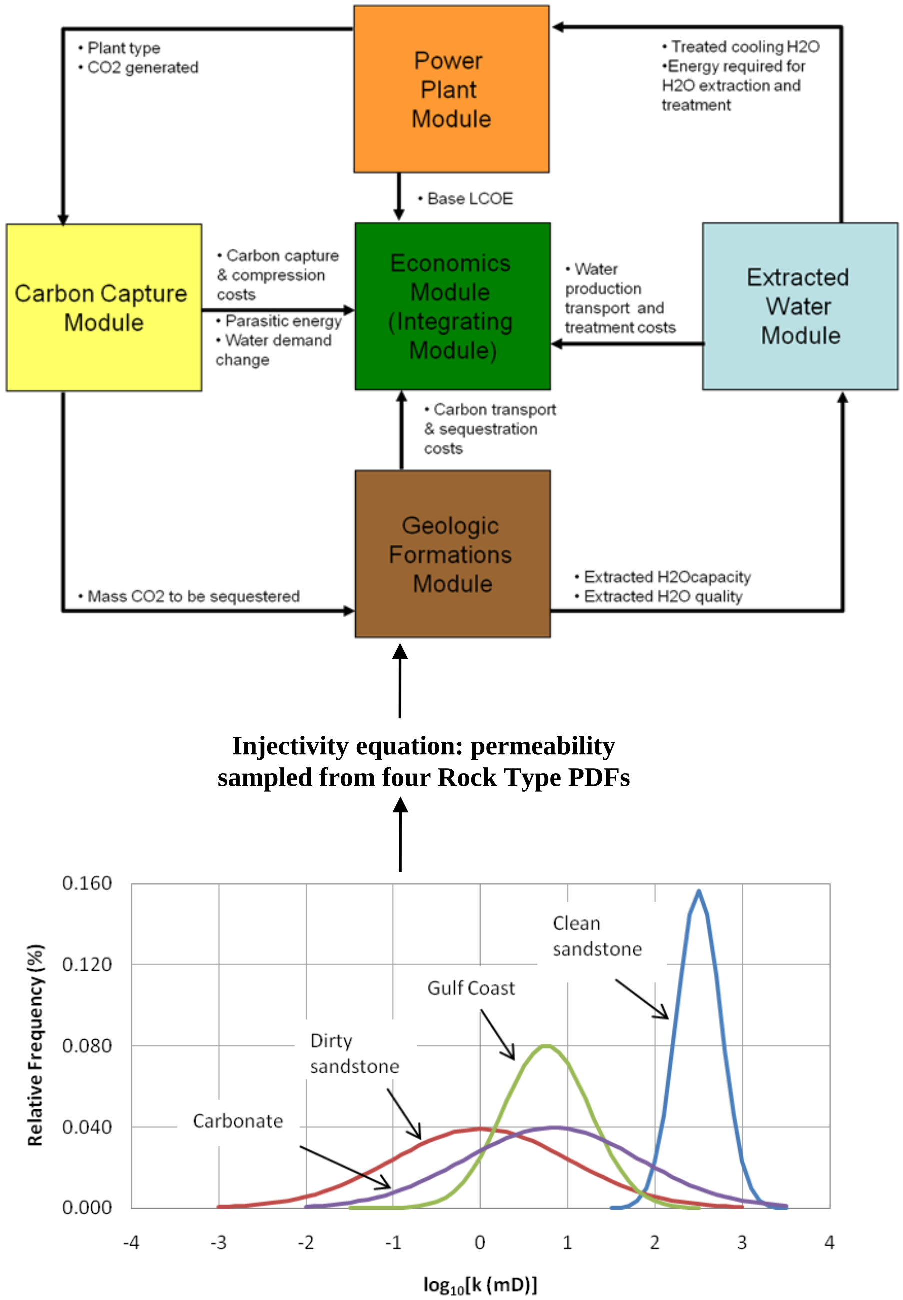

Figure 1. Schematic of the WECSsim modules and their interactions. The upper portion of the figure shows the major linked modules, whereas the lower portion displays key components of the Geologic Formations Module using permeability Probability Distribution Functions (PDFs).

2. Carbon Storage Module and Geologic Formations

Injectivity is one of three major criteria for choosing suitable CO_2 storage sites (the other two being storage capacity and containment; Pooladi-Darvish et al., 2011). It is the flow rate of an injectant (e.g., CO_2) normalized by the pressure difference between the well and the formation. Permeability is a key parameter in mathematical expressions of injectivity, in large part because of its order of magnitude variability for rock types of interest for CO_2 storage, especially sandstones and carbonates (e.g., see Kupecz et al., 1998). In particular, absolute permeability is a rock-specific property that reflects the ease of fluid flow.

Relative permeability accounts for mutual interference in flow due to the presence of two or more fluids in the porous medium (Domenico and Schwartz, 1998). Permeability relates gradients in pressure and elevation to flux of a fluid of interest:

$$q_i = -\frac{k k_{ri}}{\mu_i}\left(\nabla P_i - \rho_i g \nabla z_i\right) \tag{1}$$

where the subscript *i* represents the fluid (i.e., CO_2 or brine); *k* is absolute permeability; k_r is relative permeability (value between zero and one); *P* is fluid pressure; ρ is density; *g* is the gravitational acceleration constant; *z* is elevation; and *q* is the volumetric flux (m^3/m^2) of the fluid through a porous medium.

Inaccurate estimation of permeability and its spatial variability can lead to unreliable predictions of injection rates. For example, the West Pearl Queen depleted oil reservoir CO_2 injection test in New Mexico involved predictive reservoir simulation of injection rates based on available downhole wireline log and core data (Pawar et al., 2006). Simulated injection rates of 100 metric tonne/day were much higher than the measured 40 metric tonne/day, which Pawar et al. (2006) interpreted as indicating lower than expected permeability and higher than expected reservoir pressure. Thus, suitably accurate prediction of injectivity and its potential decline during the life of a CO_2 storage project is needed to achieve the physical goals of desired storage rates.

The Geologic Formations Module of WECSsim calculates CO_2 injection flow rates, or injectivity per well, into geologic formations located throughout the United States. A key output is the number of wells needed to meet total injection rates associated with a capture scenario specified by the WECSsim user. WECSsim then uses the numbers of wells to estimate injection-related costs. Formation and fluid properties strongly govern flow rates, as outlined above, which in turn affect the number of required wells. To minimize computational expense, WECSsim uses an analytical solution for injection into a cylindrical, homogeneous, isotropic domain under quasi-steady state or “middle time region” flow conditions (Bryant and Lake, 2005; Wattenbarger, 1987):

$$I = \frac{4\pi k k_r H}{\mu\left(\ln\left(\frac{4A}{1.781 C_A r_w^2}\right) + 2s\right)} \tag{2}$$

where *I* is injectivity or flow rate of injectant (i.e., CO_2) divided by a pressure gradient (i.e., downhole pressure at the well minus the average reservoir pressure); *k* and k_r are absolute and relative permeabilities, respectively; *H* is the vertical thickness of the formation; μ is viscosity of the injectant; C_A is a shape factor; *A* is the area flooded by the injectant; r_w is the wellbore radius; and *s* is a skin factor. The shape factor reflects the geometry of the flooded zone (see Wattenbarger, 1987), whereas the skin factor represents a zone of permeability reduction near the wellbore due to possible formation damage, precipitation, or other processes. Currently, we assume the skin factor is zero (i.e., we assume no formation damage near the wellbore).

Equation 2 neglects spatially varying flow properties of absolute and relative permeability and capillary pressure (i.e., the pressure difference between CO_2 and brine due to capillarity). However, as mentioned above, such spatially varying parameters impact injectivity. To incorporate heterogeneity, WECSsim samples probability distribution functions (PDFs) of absolute permeability when applying the injectivity equation (see Fig. 1), resulting in probabilistic output. An approach to include spatially varying heterogeneity, not presented in this paper for simplicity, but already developed within WECSsim, incorporates upscaling of geostatistical realizations of permeability and porosity. These upscaled realizations are used to drive the injectivity equation, which is then validated by numerical reservoir simulations with TOUGH2 (Pruess et al., 1999) that include spatially varying relative permeability and capillary pressure.

Properties for several formations within the United States were initially to be populated within WECSsim with data from the 2008 version of the National Carbon Sequestration Database (NatCarb) (National Energy Technology Laboratory, 2008). However, NatCarb 2008 lacks sufficient porosity and permeability data for many formations. Thus, we have defined four rock types based on lithology. All 325 NatCarb “polygons” or formations have been assigned to the Rock Types: 1) sandstone; 2) dirty sandstone; 3) carbonate; 4) Gulf Coast; or some combination of these. These Rock Types are described by probability distribution functions of permeability, porosity, and spatial correlation properties (see Appendix 1 and Fig. 1). Thus, WECSsim can call any NatCarb formation, and by its association with a Rock Type (or combination of Rock Types), perform the injection rate calculations for the formation. The size of the formation is given by areal projections (i.e., polygons) in the NatCarb database and average formation thickness.

3. Scenario Results

The WECSsim model takes user input on target CO_2 capture at a given power plant and then calculates the costs that would be associated with storing the captured CO_2 in each of 325 NatCarb 2008-based geologic polygons. In this analysis we explore the impact of permeability (as driven by rock type) of the polygons by fixing all other WECSsim variables including the power plant considered. For consistency with previous analyses (Kobos et al., 2011a,b), we evaluate the San Juan Generating station (1848 MW, 77% capacity factor, 2102 lb CO_2/MWh) with 90% CO_2 capture, or approximately 11 million metric tonne per year of CO_2 to be stored. Whereas typically, the CCS costs associated with this generating station would be driven by distances between the station and the potential storage, for the purposes of this analysis we force all distances and other formation specific properties with the exception of rock type (and thus permeability) to be equal. In this way we are essentially modelling a 11 million metric tonne per year CO_2 source that overlies any of the formation geologies associated with the 325 NatCarb 2008 based polygons. To accomplish this we take advantage of WECSsim user-interface inputs that allow default properties of the polygons to be over-ridden by the model user. Specifically, the distance from the power plant to all polygons is set to zero, the footprint area of all polygons is set to 1000 square miles, the storage depth to 5000 feet, the thickness of all polygons to 500 feet, the background temperature and pressure of all polygons to 100°C and 150 atmospheres respectively, the porosity of all polygons to 15%, and a sweep efficiency of 2% (Cavanagh et al., 2010) is used for all polygons. Finally, WECSsim is set to assume that all bore holes will result in useable injection wells.

WECSsim randomly samples the permeability PDFs associated with each polygon 50 times. For polygons representing a mix of rock types, the rock type of each individual realization is set randomly based on the proportion of that rock type in the polygon. For example a polygon with an estimated mix of 70% clean sandstone and 30% dirty sandstone would sample the clean sandstone approximately 70% of the time, or 35 out of 50 realizations, and dirty sandstone for the remaining realizations. Each of these realizations of permeability is then considered the average permeability of an injection well, and WECSsim calculates an associated injectivity. Next, WECSsim solves for the flow and the well bottom pressure, that satisfies both the pipe flow equation describing pressure drop as a function of flow through the injection well casing, and the injectivity equation describing flow into the formation as a function of the pressure gradient from well bottom to background pressure. In this way, each random realization of permeability is assigned a volumetric flow rate, which when converted with density to mass flow rate describes the amount of CO_2 that can be injected with that well. WECSsim then accumulates wells discretely until they account for the entire mass of CO_2 requiring storage. If more than 50 wells are required, due to a current software limitation, WECSsim cycles through the same 50 wells again. As can be seen in Fig. 2, there is a clear nonlinear relationship between the geometric mean permeability of the suite of injection wells utilized and the injection costs. This relationship is similar to that of Keating et al. (2011), who presents results of a similar hybrid systems model that focused on mesoscale or regional scale assessment of CO_2 storage in the Piceance-Uinta Basin, CO and UT. The higher costs of Fig. 2, in comparison with Keating et al.'s result, probably result in part from investigating lower permeabilities.

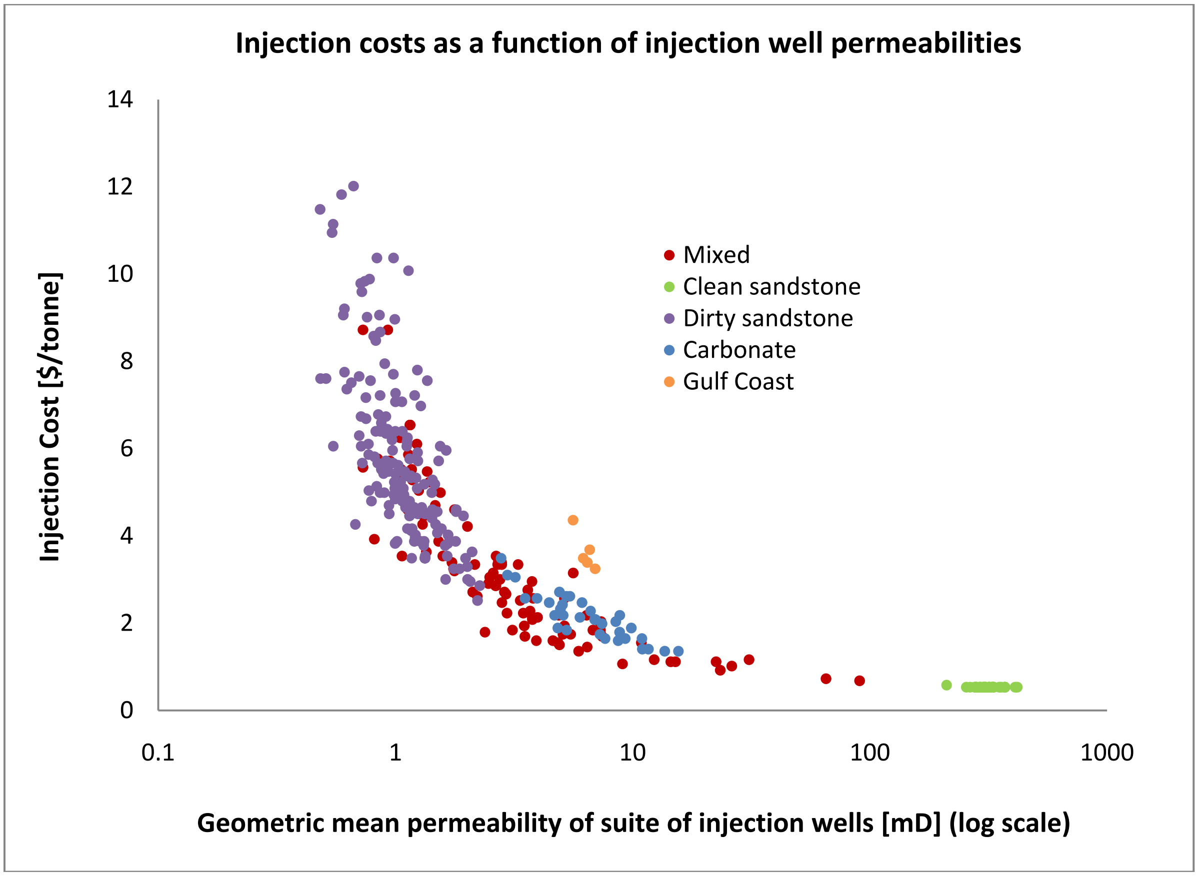

Figure 2. Relationship between the geometric mean permeability of injection wells used in each of 325 polygons targeted for storage of 11 million metric tonnes of CO_2 per year. The spread results from a stochastic sampling of permeability distributions, and increases to the left where geologic properties outstrip pipe flow constraints in controlling flow into the formation. Each point represents the geometric mean of the total number of injection wells required for a given polygon (a number that varies from 11 to 323, directly influencing injection costs (2010 $US)).

The spread seen in Fig. 2 is a result of stochastic sampling of permeability distributions and increases to the left where, at low permeabilities, flow is controlled by geologic properties as opposed to the right where permeability is high and energy losses through the well pipe become more important. The large increase in required wells as the permeability decreases drives the relatively large increase in CO_2 injection costs. In this scenario, each additional injection well adds about 4.85 cents per tonne to the total injection costs. Thus, the average required injection wells for the WECSsim simulations at a cost of $4/tonne is 83 wells, while the clean sandstone formations with geometric mean permeabilities above 100 mD each only require 11 injection wells, resulting in injection costs of only $0.53/tonne.

The Gulf Coast group of formations are slight outliers in Fig. 2, suggesting a geometric mean permeability that is not representative of the injectivity of the formations in the same way that it is for the other rock types. This effect has not been explored further but may be a result of the interaction between the statistical distribution of permeabilities used as representative of the Gulf Coast group (see Fig. 2) with the injectivity and pipe flow equations used here. The Gulf Coast group permeability spread is smaller than that of the carbonate or dirty sandstone rock types, while the clean sandstone rock types are dominated by the pipe flow equation.

Figure 3 shows the injection costs associated with the national distribution of formations defined in NatCarb 2008. As can be seen there, less than 10% of the formations have been classified as pure clean sandstone, the highest value formation in our assessment. The next least expensive options are the carbonate and Gulf Coast formations respectively, with dirty sandstone being the most costly option. Mixed formations span the range between the pure end members. Injection of CO_2 into approximately half of the formations will cost less than $4 per tonne of CO_2, with the high permeability clean sandstone eight times less. Future work looking at national CO_2 capture and storage scenarios will address how accessible and how large the high value formations will be with respect to the national fleet of power plants. This will define what role they might play in the overall national supply curve for reduced atmospheric CO_2 emissions through CCS.

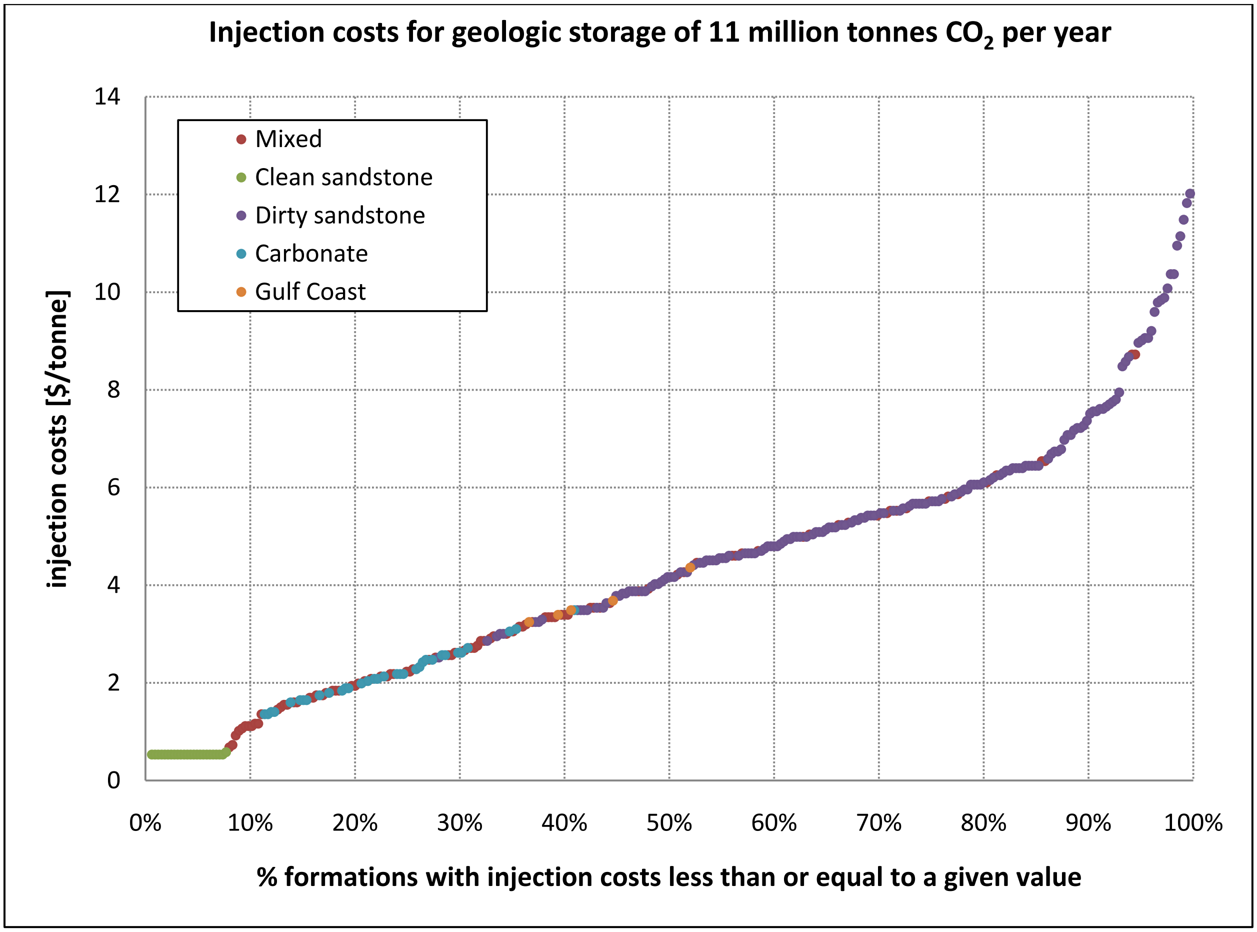

Figure 3. One realization of injection costs estimated for permeabilities associated with each of the 325 NatCarb 2008 based polygons arranged in ascending order. The low cost formations are the clean sandstone formations, followed by carbonate and Gulf Coast formations, with dirty sandstone being the most costly option.

Injection costs per tonne of CO_2 injected range over an order of magnitude from as little as $0.54 per tonne to as much as $12 per tonne. This range is driven by the national rock type distribution used in WECSsim of 8% clean sandstone, 12% carbonate or Gulf Coast, 51% dirty sandstone, and 29% mixed. This range represents substantial, geologically-based uncertainty even within the context of overall CCS costs of $45 to $56 per tonne CO_2 stored. Figure 4 shows the range of costs added by injection in relation to overall CCS costs. The overarching results presented in Fig. 4 illustrate two central notions. First, the relative contribution of the injection cost of CO_2 to total costs are potentially small, representing on their own as little as 1% of a given CO_2 source-to-sink combination. Second however, this cost information varies tremendously based on sink geology and may represent as much as 20% of total costs in extreme situations. Thus it is critical to account for geological uncertainty in as rigorous a manner as possible.

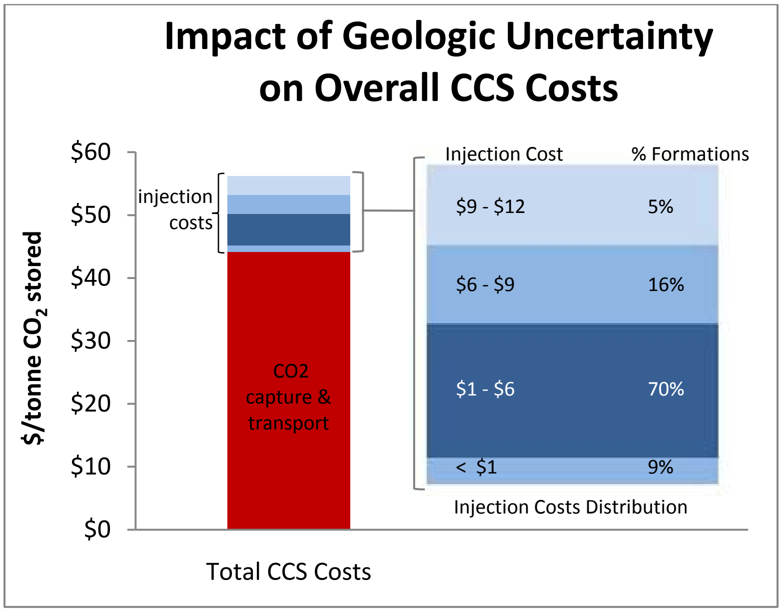

Figure 4. The range of costs added by injection in relation to overall CCS costs. In this realization, 9% of formations would involve between $0.54 and $1.00 per tonne CO_2 in injection costs, 70% would involve between $1.00 and $6.00, 16% would involve between $6.00 and $9.00, and 5% more than $9.00 per tonne of CO_2. This range is driven by the national rock type distribution used in WECSsim.

4. Discussion and Conclusions

These results have broad implications on both the number and spacing of CO_2 injection wells that may be required to store emissions from a stationary source. Low injectivity will result in both additional injection wells, and dense well spacing in a well field. Site characterization of permeability thus becomes extremely important in initially selecting potential geologic targets for CO_2 storage. Order of magnitude ranges in permeability may be likely for some geological environments (e.g., fluvial depositional systems), and the occurrence of low permeability zones can render a particular injection well relatively ineffective. If permeability is overestimated in original site characterization, many more wells will be required to inject and store a given amount of CO_2 than originally assumed, potentially shifting the economic viability of a given target formation substantially. This work suggests that geological properties may negatively affect the potential cumulative amount of physically and economically-viable CO_2 storage resources in the U.S. (e.g., less storage space supply for a given cost to inject and store CO_2) to a substantial degree.

The system performance and cost results presented in this analysis compare favourably to those in the literature; however, this work presents additional formation type-specific information when developing the CO_2 storage supply curve. The work of Dooley et al. (2004) present a North American storage supply curve assessment driven by the demand for CO_2 storage from a subset of power plants and not necessarily by the potential physical pore space available for CCS. Therefore, their space estimates for CO_2 storage supply are much lower than that presented here, their CCS costs do not include capture and compression considerations which dominate the economics, and they assume an annual injectivity per well of approximately 200,000 tonnes/CO_2/well/year. Their cost curve for power plants within 250 miles of a representative formation for storage, for example, ranges from $0 to $60/tonne CO_2 for between 3,000 and 3,500 $MtCO_2$ stored annually.

The range of potential (or often described as theoretical) storage capacity in Deep Saline Formations ranges from 1,840 $GtCO_2$ for the U.S. (Dahowski et al., 2011) to between 400 – 10,000 Gt globally (IEA, 2006). There is considerable uncertainty associated with these assessments, and much of the literature points to the need to improve the assessment methodology and therefore capacity estimates (Bachu, 2007, 2008; Eccles et al., 2009; McCoy and Rubin, 2009; Thibeau and Mucha, 2011). This is where the work presented here looks to increase the accuracy of the potential CCS information by focusing on the uncertainties within the geological properties, and how this uncertainty propagates into the cost estimates. The range of storage costs for the work presented here are 45 to 57 $/tonne of CO_2 for capture, compression, and injection of 11 million metric tonnes of CO_2 per year from a single source into a geologic formation while varying its permeability over the range expected for storage targets throughout the U.S. This analysis is for a single source to any sink, and costs will be expected to rise as we begin to consider multiple sources, each targeting its own least cost sequestration option in the presence of competition for the highest value formations. Specific sinks for CO_2 with favorable conditions (e.g., high permeability, relatively large in size, high confidence storage potential, etc.) will be expected to be attractive to multiple sources of CO_2.

In the important and ongoing effort to quantify expected costs associated with CCS, the level of uncertainty can present a substantial challenge. This uncertainty comes from many directions including technological, regulatory, and arguably most substantial, geological. Within geological uncertainty, the connection between permeability and injection costs is a critical intersection between the incredible uncertainty and natural variability inherent in the deep subsurface, and the bottom line costs which will be so important in scale up efforts relating to CCS. This paper has provided insight into the range of cost variability to injection costs that will result from current best available estimates of the properties of the deep saline formations in the United States as potential targets for long term CO_2 sequestration.

5. Ongoing and Future Work Efforts

Our major goal is the full development of a flexible model, namely WECSsim, that can assess costs and economics at the scale of the contiguous United States. The model will produce knowledge on what factors drive cost and limit the physical feasibility of injection and storage. A capability under development includes simultaneous CO_2 injection and brine extraction for reservoir pressure management and/or beneficial aboveground use through brine purification. WECSsim also will include CO_2 injectivity and brine extractivity methods that incorporate heterogeneity in relative and absolute permeability, porosity, and capillary pressure through upscaling of geostatistical realizations of reservoir properties. We envision the model being used for multiple tasks, including development of national-scale cost curves and identification of the most promising project locations under user-defined constraints. The costs curves will be developed across the existing fleet of power plants to evaluate potential policy scenarios of what it would take to begin to drive CCS with a market mechanism, and how much storage such a mechanism might be expected to create. These scenarios would also provide information on which formations would be targeted by what power plants in what order, identify those that could be used to drive optimized network models, and to evaluate potential economy of scale savings associated with coordinated pipeline construction that could be used to drive costs down. We see WECSsim as an additional work contributing to the body of research already developed by NatCarb 2008 and the regional CO_2 partnerships (Litynski et al., 2009) that are looking to assess specific sites for CO_2 storage. For example, the model user could choose to sequester some amount of CO_2 in the Midwest, with or without brine extraction, and the model would identify sources of CO_2, potential sinks, and associated capture and injection- and/or brine-extraction-related costs to facilitate decision making. We are also in the process of generating cost curves for the 325 NatCarb formations/polygons that reflect the depth, thickness, distance from power plants, and other specific properties of the formations.

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Appendix

Our approach for coping with NatCarb 2008 data limitations is based on assigning the 325 polygons, which represent formations or groups of formations, to a small set of rock types with well defined (i.e., quantitative) properties in terms of porosity and permeability PDFs, and spatial structure properties (i.e., nugget, sill, and ranges of a semivariogram). The data for four Rock Types are presented in Table A1 for incorporation into WECSsim for flow rate estimation. Thus, WECSsim is able to perform the flow rate calculations for all the polygons, based on the small number of rock types.

WECSsim requires pdfs, not data ranges of permeability, as given Table A1. The permeability and porosity ranges are converted to PDFs through the following assumptions:

- arithmetic porosity values are assumed to be normally distributed;
- the $\log_{10}$ transformation of permeability values is assumed to be normally distributed; and
- the data ranges for porosity and $\log_{10}$ permeability are assumed to fall near the upper and lower tails of the normal distributions.

Due to time constraints and limited data availability, we are not able to obtain the sample populations (e.g., number of core plugs for porosity measurements), the depth of the samples, and other information to determine where the minimum and maximum values of the data fall in the assumed normal distributions. Furthermore, we are not evaluating whether the data are normally distributed. However, previous work has indicated that permeability data for geologic formations are typically $\log_{10}$ normal (Hoeksema and Kitanidi, 1985). To facilitate implementation in WECSsim, we assume that the mean of each PDF is the average value, respectively, of the minimum and maximum values of the ranges of porosity and $\log_{10}$ permeability (in this context, range refers to minimum and maximum data values and not the range of a semivariogram). We assume that the minimum and maximum values of the ranges of porosity and $\log_{10}$ permeability fall two to three standard deviations away from the mean of the range (Table A1).

Table A1. Quantiative defintion of the four Rock Types.

Permeability (mD)

Rock Type	min.	max.	$\log_{10}$ min.	$\log_{10}$ max.	$\log_{10}$ mean	σ for min. & max. at 3σ	σ for min. & max. at 2σ
Clean Sandstone	100	1000	2.00	3.00	2.50	0.17	0.26
Dirty Sandstone	0.01	100	-2.00	2.00	0.00	0.67	1.02
Gulf Coast	0.60	54	-0.22	1.73	0.80	0.33	0.50
Carbonate	0.07	621	-1.15	2.79	0.80	0.66	1.01

Porosity

Rock Type	Min.	Max.	Mean	σ for min. & max. at 3σ	σ for min. & max. at 2σ
Clean Sandstone	0.08	0.18	0.13	0.017	0.026
Dirty Sandstone	0.09	0.27	0.18	0.030	0.046
Gulf Coast	0.012	0.15	0.081	0.023	0.035
Carbonate	0.001	0.28	0.14	0.047	0.071

Semivariogram

Rock Type	Nugget	Sill	Horizontal Range (m)	Vertical Range (m)	Poros.-perm. coeff. r
Clean Sandstone	0.20	0.80	15000	10	0.6
Dirty Sandstone	0.26	0.74	2000	4	0.5
Gulf Coast	0.30	0.70	1500	3	0.4
Carbonate	0.22	0.78	32350	7	0.6

Note: Nugget and sill values were scaled such that their total equals 1 for input into GSLIB (Deutsch and Journel, 1992). The dirty sandstone uses the nugget, sill, and range values from Finely (2005) for the Mt. Simon Sandstone.