Impacts of Geological Variability on Carbon Storage Potential

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Dissertation submitted in partial fulfillment of the requirements for the degree of Doctor of Philosophy in the Department of Earth and Ocean Sciences in the Graduate School of Duke University

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Abstract
The changes to the environment caused by anthropogenic climate change pose major challenges for energy production in the next century. Carbon Capture and Storage (CCS) is a group of technologies that would permit the continued use of carbon-intense fuels such as coal for energy production while avoiding further impact on the global climate system. The mechanism most often proposed for storage is injection of CO$_2$ below the surface of the Earth in geological media, with the most promising option for CO$_2$ reservoirs being deep saline aquifers (DSA’s). Unlike oil and gas reservoirs, deep saline aquifers are poorly characterized and the variability in their properties is large enough to have a high impact on the overall physical and economic viability of CCS. Storage in saline aquifers is likely to be a very high-capacity resource, but its economic viability is almost unknown. We consider the impact of geological variability on the total viability of the CO$_2$ storage system from several perspectives. First, we examine the theoretical range of costs of storage by coupling a physical and economic model of CO$_2$ storage with a range of possible geological settings. With the relevant properties of rock extending over several orders of magnitude, it is not surprising that we find costs and storage potential ranging over several orders of magnitude. Second, we use georeferenced data to evaluate the spatial distribution of cost and capacity. When paired together to build a marginal abatement cost curve (MACC), this cost and capacity data indicates that low cost and high capacity are collocated; storage in these promising areas is likely to be quite viable but may not be available to all CO$_2$ sources. However, when we continue to explore the impact of geological variability on realistic, commercial-scale site sizes by invoking capacity and pressure management constraints, we find that the distribution costs and footprints of these sites may be prohibitively high. The combination of issues
with onshore storage in geological media leads us to begin to evaluate offshore storage potential. By considering the temperature and pressure regimes at the seafloor, we locate and quantify marine strata that has “self-sealing” properties, a storage option that we find is plentiful off the coasts of the United States. We conclude that further research into transport optimization that takes into account the true variation in geological media is necessary to determine the distribution of costs for carbon capture and storage to permit the full evaluation of CCS as a mitigation option.
Dedication

This dissertation is dedicated to my parents, John and A.J. Eccles.
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1. Introduction

1.1 Climate Change Mitigation

In the next century, the impact of global climate change on ecosystems, biodiversity, and human civilization is expected to become significant. The best efforts at determining the scientific consensus on the issue of global climate change, reported by the United Nations (UN) Intergovernmental Panel on Climate Change (IPCC), thus far indicate that anthropogenic greenhouse gas (GHG) emissions are the major cause of large-scale shifts in climate over the past century. More importantly, these changes are likely to continue and accelerate over the next century if observable trends in population growth, energy use, and energy technology continue (Bernstein et al. 2007).

The negative impacts of climate change range from loss of biodiversity and changes in water availability to large shifts in arable land, weather patterns, and massive flooding (Bernstein et al. 2007). Detailed in reports by the IPCC, the sum of scientific literature on the subject has led scientists, stakeholders, and policymakers to consider attempting to mitigate climate change or its effects in a variety of ways. Changes in energy capital, energy consumption, land-use practices, and so on might alter the course of future emissions and reduce the rate at which anthropogenic GHG emissions change Earth’s climate (Bernstein et al. 2007).

Although it is not the most potent greenhouse gas, Carbon Dioxide ($CO_2$) has the greatest impact on climate of the anthropogenic GHG emissions, as $CO_2$ emissions are orders of magnitude larger than other GHG emissions (Bernstein et al. 2007). Global emissions of $CO_2$ are nearly 30 gigatonnes (Gt) per year, with the United States contributing roughly 6 gigatonnes per year of that total (EIA 2010a). Much of the CO$_2$ released into the atmosphere is produced by energy production, as most global energy
infrastructure is based on fossil fuels (Bernstein et al. 2007). For example, in the United States, electricity production accounted for 2.1 Gt of 5.4 Gt total CO₂ emissions in 2009, and 2.4 Gt of 5.8 Gt in 2008 (EIA 2010a).

As part of the energy services system, electricity production is particularly important from a mitigation perspective because it is essentially a choke point for energy flow. Transportation emissions in the United States are nearly 1.9 Gt, almost all of which are from relatively carbon-intense petroleum (EIA 2010a). However, these emissions are produced by hundreds of millions of vehicles, each of which was fueled by petroleum extracted from millions of wells and sent through a complex distribution system of thousands of pipes, ships, trucks, and refineries to its end use.

The electricity sector generates over half of its useful energy from coal, another carbon-intense fuel that, like petroleum, is produced from different extraction points. This coal use accounted for 1.7 of the 2.1 Gt of electricity sector emissions in 2009 (coal accounted for 1.8 Gt in total in 2009), roughly on par with petroleum emissions in the transportation sector (EIA 2010a; EIA 2010b). Yet these emissions were produced by just under 600 coal plants, each of which produced an average of roughly 10,000 tonnes of CO₂ per day (EIA 2010a; EIA 2010b). By contrast, each passenger vehicle in the United States produces about 10 tonnes of CO₂ per year (EIA 2010a). The concentration of point sources of CO₂ for electricity production (especially those fueled by coal) is similar, notably in India, China, and Japan (International Energy Agency Greenhouse Gas R&D Programme 2002).

This makes CO₂ emissions from (coal-fired) power plants an especially attractive mitigation target. Eliminating or controlling emissions from these few sources would make a major impact on U.S. CO₂ emissions. As such, it is an important option for the
United States, constituting a potential “wedge” (in the parlance of Socolow and Pacala) for climate change mitigation (Pacala & Socolow 2004). Changing from coal- to natural gas-fired power plants would reduce CO$_2$ emissions in the United States by almost 15% and eliminating coal-fired power production entirely would reduce CO$_2$ emissions to 20% below 1990 levels (EIA 2010a; IPCC 2005).

Such a switch is unlikely, however, because coal is an extremely cheap, reliable fuel for electricity generation. Since 1949, the average price of coal has actually gone down in real dollars, to about $1.50 per mmBTU in 2009 (EIA 2010a). By contrast, the price of natural gas (at the city gate) was $5.75 and petroleum (at only $50 per bbl) was $8.85 per mmBTU (EIA 2010a). Coal-fired power plants average over 40 years in age and still constitute 314 gigawatts of net summer capacity, producing 1.76 billion kilowatthours in 2009 (EIA 2010a; Environmental Protection Agency (EPA) 2007). Coal plants are run at high capacity factors because of low ramp rates and since many of them are fully amortized, can sell electricity at the cost of fuel and operations and maintenance (O&M), which for a plant with 35% efficiency is only 2 cents per kWh (EIA 2010a). Coal is also extremely abundant in the United States, with 488 billion tonnes (roughly 10,000 quads or 1e19 BTU) in the demonstrated reserve base (DRB) (EIA 2010).

If policymakers and stakeholders in the United States decide to impose serious limits on CO$_2$ emissions, coal-fired electricity may be less attractive both to electricity producers and consumers (Bernstein et al. 2007; Katzer et al. 2007; IPCC 2005). US coal use, however, is relatively clean in other respects. In developing countries, where coal, wood, and animal dung are often burned indoors with poor ventilation, chronic respiratory diseases caused by air pollution account for nearly 3 million deaths (mostly women and children) per year (World Health Organization (WHO) 2010). In the United
States, strict controls on fly ash, NO\textsubscript{x}, and SO\textsubscript{x} emissions from power plants have reduced negative impacts from coal combustion on human health and the environment dramatically (EIA 2010a; Katzer et al. 2007). These emissions have been reduced with emission controls technologies such as fly ash filters and flue gas desulfurization units that extract the pollutants from the exhaust of the combustion process. If similar emissions control technologies can be implemented cheaply for large CO\textsubscript{2} sources (primarily coal-fired power plants), coal can continue to be utilized as a cheap, local resource without impacting the global climate (IPCC 2005; Katzer et al. 2007).

### 1.2 Carbon Capture and Storage

The system for controlling carbon dioxide emissions from point sources is called carbon capture and storage or sequestration (CCS). A CCS system would have two major elements: a technology or control system that would capture CO\textsubscript{2} from the source and a storage system that would sequester the CO\textsubscript{2} more or less permanently outside of the carbon cycle (Howard J. Herzog 2001; IPCC 2005).

#### 1.2.1 Capture

The capture system could come in many forms, primarily among them pre- and post-combustion capture (IPCC 2005). In the former, via chemical, thermal, or physical processes, the carbon in fossil fuels is separated prior to combustion. One technology for doing so is integrated gasification, in which carbon-heavy fuels are reformed into carbon monoxide and hydrogen, which are easy to separate post-combustion into CO\textsubscript{2} and water vapor. This technology has been implemented twice (successfully) in the United States, with more plants slated to come online in the 2012-2020 timeframe (IPCC 2005; Department of Energy (DOE) 2010). In the latter, CO\textsubscript{2} is separated from the flue
gas produced by a combustion process. The most well-understood technology for doing so is to use an amine-based solvent; flue gas bubbled through the solvent will have its CO₂ dissolved (Howard J. Herzog 2001; H. Herzog et al. 1991). By heating the solvent, the CO₂ can be released, and the solvent reused. Chilled ammonia is also under consideration for post-combustion capture (IPCC 2005). A hybrid option is oxy-fuel combustion, in which air with high oxygen content is used in the combustion process; because of the higher resulting combustion temperatures, the flue gas has a higher partial pressure of CO₂ than normal combustion (IPCC 2005).

1.2.2 Storage

All of these options would produce a relatively pure stream of CO₂ which would have to be stored somewhere. At an average of 10,000 tonnes per day, this would produce 5 billion liters of gas per power plant per day at atmospheric pressure (IPCC 2005; Span & Wagner 1996). Generally, the capture process is understood to include compression to a supercritical fluid. Supercritical fluids retain the viscosity and compressibility of a gas but have the density of a liquid. CO₂ is a supercritical fluid at 7.1 MPa and 31 deg C, at which its density is 468 kg/m³. Nonetheless, a power plant would still have to dispose of 20 million liters of supercritical CO₂ per day (IPCC 2005; Span & Wagner 1996).

1.2.2.1 Geological Storage

This disposal can happen in a number of ways, generally referred to as storage or sequestration (IPCC 2005). First proposed several decades ago, the leading option is injection into geological formations underground (Koide et al. 1992). Geological formations have void or pore space between mineral grains that are in some cases highly interconnected (Suppe 1985; Bahr et al. 2001). The formations tend to become saturated
with fluid, generally water that was either buried with the rocks or has slowly moved downward over time. Oil and gas can also become trapped in these pore spaces despite their tendency to move upward because of their buoyancy (IPCC 2005).

Supercritical CO$_2$ is likewise less dense than the water saturating these rock formations (together referred to as aquifers), but can be trapped just like oil or gas. The primary trapping mechanism is an impermeable rock formation just above the reservoir to prevent upward migration of the CO$_2$, although over time the CO$_2$ may dissolve into the pore fluid and possibly mineralize (solubility trapping appears to be the dominant long-term trapping mechanism) (IPCC 2005; John Bradshaw et al. 2007; Gilfillan et al. 2009).

CO$_2$ storage in geological media of this form could involve several different types of rock. Like oil and gas reservoirs, these rock formations would ideally have highly interconnected pore space (i.e. high permeability or hydraulic conductivity) below a layer of impermeable cap rock. Typically, this occurs in sedimentary formations in which a layer of sandstone is capped by a layer of mudstone or shale. Because of the similarity between oil and gas reservoirs and the hypothetical requirements of a CO$_2$ storage reservoir, depleted oil and gas reservoirs (from which it is difficult to extract more oil) are considered a good option for storage of CO$_2$ (IPCC 2005; Howard J. Herzog 2010; Department of Energy (DOE) 2010).

These reservoirs are relatively well characterized and in some cases have already had CO$_2$ injected into them in enhanced oil recovery (EOR) systems (IPCC 2005; Department of Energy (DOE) 2010). Because of supercritical CO$_2$’s high miscibility, it is an extremely good solvent, and reduces the viscosity of petroleum, which is often a barrier to efficient extraction of oil (IPCC 2005; Department of Energy (DOE) 2010). CO$_2$
can also be used to pressurize underground gas formations to increase recovery rates (IPCC 2005; Department of Energy (DOE) 2010). EOR is therefore also considered an option for CO₂ sequestration, although it is unclear how the EOR concept would balance the competing requirements of improving hydrocarbon recovery (often involving recycling or loss of CO₂ outside the reservoir) and storing CO₂ permanently (IPCC 2005; Department of Energy (DOE) 2010). Since the goal of hydrocarbon recovery is generally to puncture the cap rock and get as much fluid as possible out of the reservoir, it is possible CO₂ would not remain trapped (Finley et al. 2005; Qi Li et al. 2009; Oldenburg 2007).

Oil- and gas-bearing formations are not the only option for storage in geological media. There are also sedimentary rock formations much deeper below the earth called deep saline aquifers (DSA) (IPCC 2005; Department of Energy (DOE) 2010; Howard J. Herzog 2010). Early proposals for storage of CO₂ in geological media focused on the massive bulk volume of these DSA’s as evidence of the near limitless potential for CO₂ storage in geological media (Koide et al. 1992). Saline aquifers are often more than a kilometer deep, with temperatures and pressures that maximize the density of CO₂ despite declining available pore space (Span & Wagner 1996; Athy 1930). As sedimentary formations, they are likely to contain the required permeable sandstone layers with impermeable cap rocks. The available storage in deep saline aquifers is estimated to be many orders of magnitude higher than that in oil and gas reservoirs (Stefan Bachu et al. 2007; Department of Energy (DOE) 2010; Stefan Bachu 2008; Nordbotten et al. 2005; Howard J. Herzog 2010).

Storage in similar carbonate formations is often lumped together with sandstone saline aquifers, although storage in carbonate poses unique challenges. Because of the
geochemical interactions between CO$_2$ (especially CO$_2$ dissolved in water, also known as carbonic acid) and carbonates, this method of storage may be considerably less safe than that in saline aquifers and hydrocarbon reservoirs. Since the rock matrix may simply dissolve upon contact with CO$_2$ (especially at supercritical temperatures and pressures), groundwater contamination may be a serious concern, not just from CO$_2$ leakage itself but also from metals that would make their way into groundwater having been leached from carbonate rock matrices (Little & Jackson 2010).

Alternate options for geological storage include unmineable coal seams (UCS) or enhanced coalbed methane (ECBM). In coal seams, methane adsorsbs to the coal itself, which is why methane is often produced by coal mines or causes safety concerns (Department of Energy (DOE) 2010). In this form of carbon storage, CO$_2$ is injected into coal seams; the carbon dioxide is preferentially adsorbed and will take the place of the methane; obviously the methane must be captured or this method would be a massive loss in terms of global warming potential. This storage mechanism is relatively poorly understood and its total potential appears to be limited (compared to saline aquifers) (Department of Energy (DOE) 2010).

Finally, storage in basalts or with mineralization on the surface may also be an effective onshore sequestration option. Of all the potential storage mechanisms involving geological media, this is the most poorly understood and most marginal in terms of its total potential (Department of Energy (DOE) 2010).
Figure 1: Schematic Diagram of Geological Storage Options, adapted from IPCC (2005).

Mentioned briefly above, the total potential of these storage options is important because the scale of a CCS system would be immense (Howard J. Herzog 2010). The volume of CO$_2$ emitted by large point sources in the United States in a year if compressed to supercritical density would be roughly equivalent to the volume of oil produced by the entire world in a year (EIA 2010a). Over 20 years, a typical planning horizon for the electric power sector, coal-fired power plants would emit almost 100 cubic kilometers of supercritical CO$_2$ (EIA 2010a; EIA 2007; Bock 2002). There are more than one trillion tonnes of potential CO$_2$ emissions in the U.S. coal DRB, almost 3000 cubic kilometers at supercritical density (EIA 2010a; EIA 2010).
The total storage potential of a sequestration option is therefore extremely important in evaluating its place in a CCS system (Howard J. Herzog 2001; Howard J. Herzog 2010; Stefan Bachu 2008). Except for deep saline aquifers, the total U.S. storage potential of these options are estimated to be at most in the tens of gigatonnes, a paltry 5 years of electric sector emissions (Department of Energy (DOE) 2010). The storage potential of deep saline aquifers, on the other hand, is estimated to be thousands of gigatonnes (Department of Energy (DOE) 2010; John Bradshaw et al. 2007). This estimate is likely to be somewhat optimistic for a variety of reasons, explored in detail later, but the relative scale of the DSA storage potential compared to other geological media shows that saline aquifers are the best option for long-term, large-scale storage of CO2 (Department of Energy (DOE) 2010).

1.2.2.2 Other Sequestration

This summary of onshore geological sequestration options does not include two other major categories of sequestration. One of these is biosequestration, which is a relatively amorphous concept in which long-term “storage” of CO$_2$ in organisms is encouraged somehow. Generally, this involves changing the way a community of organisms interacts with the carbon cycle, such as increasing the productivity of marine phytoplankton by adding iron, under the assumption that the plankton will be removed from the carbon cycle. Clearly, this type of sequestration is not directly compatible with the point-source CCS system, except esoteric designs involving bioreactors (Bernstein et al. 2007; IPCC 2005).

The other major category, however, has even more potential (and possibly more risk) than onshore geological sequestration: ocean sequestration. Ocean sequestration
involves the injection of CO₂ below the surface of the ocean. There are several possible mechanisms for storage(IPCC 2005; Koide et al. 1997).

The first of these is direct ocean injection. At intermediate depths, advection and dissolution would be the dominant mode of storage, although it remains unclear that any CO₂ would actually be permanently stored in such a way(IPCC 2005; Haugan & Drange 1992; Holder et al. 1995; Liro et al. 1992; Riestenberg et al. 2005). At very deep depths, roughly below 3000 meters, the temperature and pressure conditions would compress CO₂ to a liquid state that is more dense than water(Span & Wagner 1996). Gravity-driven circulation would keep the CO₂ in “lakes” at the bottom of the ocean(IPCC 2005; E. Eric Adams & Caldeira 2008; Brewer et al. 2004). At all depths, but especially those below 3000 meters, the CO₂ would likely interact with water to form hydrates (a type of solid clathrate) in which gas molecules are bound up in water crystals. These hydrates may further immobilize CO₂ and make it less vulnerable to upwelling circulation(Bacastow R.B. & Dewey R.K. 1996; Haugan et al. 2005; House et al. 2006; Holder et al. 1995; E. Eric Adams & Caldeira 2008).

As one might expect, there is considerable uncertainty as to the effect of CO₂ injection on the ocean environment and concern for benthic ecosystems alone may make this option unacceptable(Ishimatsu et al. 2004; Auerbach et al. 1997; Brewer et al. 2004). However, deep sea sediments may be utilized in the same way as onshore geological media to hold injected CO₂ (Schrag 2007; Schrag 2009; House et al. 2006). Geological formations under the ocean might even rely on density-driven circulation and hydrate formation zones below the surface of the ocean floor to keep CO₂ sequestered, bypassing the need for an impermeable cap rock(House et al. 2006). Injection into deep-sea basalts for mineralization is also an option(Goldberg & Slagle 2009; Goldberg et al. 2008;
Goldberg et al. 2010). With the volume of sediments available in the deep ocean, the capacity for this type of ocean storage is likely to be enormous (Schrag 2009; Shih et al. 2009; Divins 2010).

### 1.2.3 Transport

In order to utilize any of these storage options, there is likely to be transport infrastructure to move CO$_2$ in a supercritical state from the sources to the reservoirs (IPCC 2005; Chandel et al. 2010; Rubin 2008). On-shore geological storage was originally envisioned as a largely on-site endeavor, since sedimentary formations are very common (Koide et al. 1992). Deep saline aquifers in particular cover vast swaths of many regions of the world, especially the United States (Department of Energy (DOE) 2010). Transport infrastructure would thus be minimal, requiring short pipelines from the source to the sink (Bock 2002). To some extent this view has persisted, with modeling of transport and storage in the United States by Dooley et al finding that nearly all large point sources are within 80 km of a storage reservoir (Dooley et al. 2004). Transport to ocean sequestration sites is slightly more complicated, including options for disposal by ship; it is likely to be much more expensive than transport over land (IPCC 2005).
1.3 Cost of CCS

The technical feasibility of a CCS system is not in doubt. All elements of the CCS system have been tested in some form or another at pilot-scale or larger, even injection into saline aquifers both on- and offshore (Department of Energy (DOE) 2010). Global- and regional-scale evaluations of sequestration capacity have been refined over the past decades and cover a wide range of estimated values (including several orders of magnitude) but converge on the conclusion that capturing and sequestering the majority of emissions from large point-sources for the foreseeable conclusion is physically possible (John Bradshaw et al. 2007). The United States in particular, with the
Department of Energy (DOE)’s Carbon Sequestration Atlas of the United States and Canada III, finds that after exhaustive research, the physical bulk volume of onshore sequestration options is well in excess of decades or even centuries of emissions (Department of Energy (DOE) 2010).

Like all mitigation options, CCS must be evaluated not only on its total mitigation potential, but also the cost of implementing the system (Bernstein et al. 2007). Some options for abatement, like demand side management and energy efficiency, are cost-effective even without any kind of limits on GHG emissions (Bernstein et al. 2007). Other options, such as renewable energy, may have a mix of costs and benefits and become viable only when a carbon limit imposes a price on CO₂ emissions (Bernstein et al. 2007). Carbon Capture and Storage may be one of the more expensive mitigation technologies, depending on the parameters of its implementation and how many externalities are captured in subsidies for its deployment (IPCC 2005; David & Howard Herzog 2000; Al-Juaied & Whitmore 2009).

### 1.3.1 Cost of Capture

The capture element of a CCS system has very little variation in the cost at which it could be deployed (IPCC 2005; David & Howard Herzog 2000; Al-Juaied & Whitmore 2009). Depending on how it is implemented (i.e. post-combustion or IGCC) and how rates of technological learning affect cost, research thus far into the technology suggest that it would be difficult to see widespread adoption of capture technology below an emissions cost of $50 per tonne CO₂ or more (Katzer et al. 2007; Howard Herzog 2000; David & Howard Herzog 2000; Al-Juaied & Whitmore 2009). Post-combustion capture is not only expensive, it also requires a great deal of energy to operate; the rated output of a plant with post-combustion capture might drop by 30% (referred to as the energy
penalty) (IPCC 2005). The heatrate of the plant is thus a primary factor in the CO₂ price at which post-combustion capture becomes viable. New IGCC plants are modeled as nearly 50% more expensive with CCS than without in the National Energy Modeling System (NEMS) used by the US DOE’s Energy Information Administration (EIA) (EIA 2007). Research by Herzog et al at MIT indicates that as capital cost estimates have only increased over the past several years (Howard J. Herzog 2010), these estimates may even be too low, a conclusion also reached by industry analyses (Al-Juaied & Whitmore 2009).

1.3.2 Cost of Storage and Transport

Nonetheless, there is not significant variation in the control technology such that one power plant has a much lower cost for installing capture equipment than another; variations in marginal costs are due almost entirely to heat rate and energy penalty for post-combustion capture (Howard J. Herzog 2010; H. Herzog et al. 1991; Howard Herzog 2000). These costs, moreover, appeared to dominate the costs for possible transport and storage by a factor of ten. Early estimates recorded by the IPCC for the cost of storage ranged from $0.30 to $8 per tonne, including offshore options, in three reports for the United States, Europe, and Australia (IPCC 2005; Bock 2002; W. G. Allinson et al. 2003; Hendriks et al. 2004). The combined cost of storage and transportation in the United States was estimated by Bock at a very low $3 per tonne (Bock 2002). In concert with increases in other cost estimates above the rise of inflation, sequestration costs have risen to $10 or above in recent estimates (Dooley et al. 2008; Middleton & Bielicki 2009; BCG 2008; McKinsey Climate Change Initiative 2008; Al-Juaied & Whitmore 2009). As such, however, they merely represent a slightly increased fraction of the total cost of the CCS system.
Missing from many of these analyses, however, is an exploration of the full range of costs that might be encountered in the storage of CO₂. A detailed document compiled for the EPA listing many of the possible expenses for a sequestration site includes many items dependent on geological properties of the storage reservoir, such as the cost per well (the number of wells depends on injection rate per well), the cost of site evaluation (a function of the surface area of the reservoir, which is dependent on reservoir geometry), and so on (Environmental Protection Agency (EPA) 2008). The reservoir properties on which these costs depend may vary over several orders of magnitude.

Analyses such as those conducted by Dooley et al and Dahowski et al use a single set of reservoir properties generalized for all saline aquifers (comprising thousands of cubic kilometers of rock) and thus a single cost of $~12 per tonne (Dahowski et al. 2009; Dooley et al. 2004).

The true variation in costs may encompass costs both above and below this figure. In fact, nearly all the estimates of cost compiled to date are likely to be representative of a realistic reservoir somewhere, which makes them plausible but perhaps not appropriate as summary statistics. A full exploration of the physical and economic potential of sequestration opportunities might reveal a distribution of costs that is poorly captured by any version of summary statistics.

This analysis is particularly critical because the transport component of sequestration depends on the suitability of reservoirs both physically and economically (Wildenborg et al. 2004; McCoy & Rubin 2008a; Gresham et al. 2010; Dooley et al. 2004; Middleton & Bielicki 2009; Dahowski et al. 2009). Since the cost of transport is a function of distance (Chandel et al. 2010), there is a tradeoff between the final cost at the sequestration site and the cost of transporting to that site. In routing CO₂
pipelines and determining the total cost of CO₂ transport, it is important to take into account the spatial variability in cost of sequestration to properly optimize the system (Wildenborg et al. 2004; McCoy & Rubin 2008a; Gresham et al. 2010; Dooley et al. 2004; Middleton & Bielicki 2009; Dahowski et al. 2009). This has not yet been implemented on a wide scale, in part because of a lack of data for geological sequestration opportunities outside of oil and gas reservoirs (Department of Energy (DOE) 2010).

1.4 Geological Variability and Carbon Storage

The research question addressed by this thesis is whether geological storage is physically and economically viable for mitigating CO₂ emissions. We focus largely but not exclusively on geological storage in the United States, where available data allows us to evaluate the concept more fully than on a global scale. Our approach is to examine geological variability and its impact on storage systems, including both physical and economic parameters of potential sequestration sites. We develop a model to evaluate the physical and economic potential of geological storage sites based on the properties of the reservoir. Since this model shows a huge range of potential costs (including several orders of magnitude) for sequestration with plausible geological conditions, we apply it to georeferenced data to evaluate the distribution of these costs in the United States. Further exploration of geological variability leads to the evaluation of the size of commercial-scale geological storage sites and how the footprint of these sites might impact their deployment. Finally, the conditions we found in onshore geological sites led us to extend the evaluation of physical potential to offshore storage.
1.4.1 Modeling Physical and Economic Potential of Geosequestration

Properties of geological formations (specifically the deep saline aquifers into which CO$_2$ might be injected) vary dramatically, with key parameters ranging over several orders of magnitude. In Chapter 1, we determine the degree to which this variability in geological properties might affect sequestration capacity and cost. Modeling the coupled geological and economic properties of the reservoir demonstrates that as one might expect, variations in reservoir properties that extend over several orders of magnitude mean that costs might extend over several orders of magnitude as well. Since CO$_2$ mitigation options are generally compared on a cost per tonne basis, we develop a cost model on a per-injection well basis, demonstrating that because injection rate varies over several orders of magnitude, the cost of CO$_2$ disposal via injection wells will also display this variation.

1.4.2 Geospatial Distribution of Sequestration Potential in the United States

Since the spatial distribution of geological properties is an important factor in deploying and optimizing a CCS system, we apply this model to geospatial data for sandstone saline aquifers in the United States in Chapter 2. Working with a subset of aquifers for which there is publicly available data (Bureau of Economic Geology (BEG) 2000; Hovorka et al. 2001), we reproduce capacity estimates published by the DOE in the NATCARB project using the model described in Chapter 1 and extend the resource evaluation by applying our economic analysis. With the full range of geosequestration cost components included, we are able to demonstrate that much of the possible variation found in Chapter 1 is in fact realized when evaluating geospatial geological data. Moreover, we find that often high capacity and low cost are co-located, although
this occurs in only a few reservoirs, not evenly distributed throughout all deep saline aquifers. Using this information to build marginal abatement cost curves (MACC’s), we can see that this collocation of high cost and low quantity skews the distribution of cost strongly, with much of the storage available for low cost but only in a few locations.

At worst, this calls into question the feasibility of CO₂ storage except in these highly desirable locations. At best, it indicates a better understanding of transport optimization is required. It is clear that carbon storage may be a low-cost mitigation option in some but not all regions of the United States.

1.4.3 Impact of Geological Variability on Geosequestration Site Footprint

Our examination of storage potential thus far, however, does not include an evaluation of the scale at which storage would be deployed if it is to make a major impact on U.S. GHG emissions. In Chapter 3, we explore the implications of geology for site development, with within-site distribution costs and total site footprint being dependent on that reservoir geology. Minimizing pressure interference between injection wells and making sure there is enough bulk volume for CO₂ storage projects requires injection well spacing in the tens of kilometers, an issue not yet confronted in scientific literature. At commercial scale, this might mean that geosquestration sites would have footprints of tens of thousands of square kilometers and within-site distribution costs on scales similar to other storage component costs. We find that although there are ways to minimize site costs and footprints, at the deployment level required to mitigate emissions, CCS may require planning to deal with social and regulatory issues that arise from massive footprints and distribution systems.
1.4.4 Global Ocean Storage Potential in Self-Sealing Marine Strata

Based on the issues identified both in Chapters 1-3 and in scientific literature to date (Schrag 2009), we look to offshore sequestration as the best solution for carbon storage in the United States and possibly around the globe. With heretofore unexplored economic implications of geological variability and the specter of vast social and resource management issues onshore, we begin to examine the potential of storage in sediments at sea with “self-sealing” storage below roughly 3000 m. The final chapter analyzes global potential of this and other types of ocean storage, making the case for deployment of carbon storage infrastructure at sea if at all. CO₂ storage in strata below the seafloor may be a safe, permanent storage mechanism that bypasses many of the issues of onshore storage. Our analysis finds that global potential for this storage type is vast, although access to it may be problematic.

1.4.5. Future Work

With spatially explicit evaluations of the physical and economic potential for geosequestration, a clear next step is to extend this modeling to include transport optimization for a complete, integrated view of transport and storage. We intend to continue to evaluate onshore geological options for sequestration, adapting our approach to other storage methods and limited data, in order to examine the spatial distribution of integrated transport and storage costs that one might find in a national CCS system. Once frameworks become available for evaluating the economics of ocean transport and storage, we can integrate all storage options into a spatial optimization model, observing the dynamics of the transport system at the national level.

The abstract cost landscape that this optimization model will represent is only one component of many that power producers must deal with in making decisions
about either siting new power production facilities or retrofitting old ones. The final step in this area of research will be using the transport and storage research as an element in a decision optimization model for power producers, allowing us to compare the entire CCS system as a mitigation option to other available technologies.
2. Modeling Physical and Economic Potential of Geosequestration

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2.1. Introduction

One potential strategy to mitigate global climate change is to capture the carbon dioxide that would normally be emitted from fossil fuel burning and sequester it in long-term, stable reservoirs. Many of the world’s energy markets (including that of the United States) are likely to have some kind of emissions control program that will impose a cost on greenhouse gas (GHG) emissions, as in the European Union. If the cost imposed on a firm for emitting carbon is more than the cost of capturing and sequestering it, and if the size of storage reservoirs is great enough to store a significant amount of captured carbon, the technology could be effective at mitigating climate change while allowing the continued use of fossil fuels (IPCC 2005).

One important factor in the cost of sequestration is variability in the storage potential of sedimentary basins. Deep saline aquifers have been proposed as a type of reservoir with significant storage potential, as they tend to be permeable sandstones and generally occur at depths where the pressure and temperature would keep carbon dioxide in a very dense supercritical state.

Interest in these reservoirs assumes that the capacity will be large and that the costs of carbon capture and storage will be competitive with alternative emissions mitigation strategies. The IPCC Special Report on Carbon Sequestration (IPCC 2005) cites three primary sources for the estimated cost of geosequestration in deep saline aquifers: Bock (2002), Hendriks (2004), and Allinson (2003). These analyses have made
generalizations that may oversimplify key variables that have significant effects on CO₂ storage potential. Static storage potential per unit volume in a given reservoir depends not only on the density (which varies with temperature and pressure (IPCC 2005; Bock 2002; Stefan Bachu 2003; Nordbotten et al. 2005)), but also on reservoir porosity (i.e. void space). Additionally, some of these studies did not consider variables that affect the rate at which CO₂ can be pumped into the reservoir. Where injection rates are considered (Bock 2002) they are derived from numerical simulations. In reality, layer thickness, permeability, and depth will likely have large effects on injection rates, and these properties can vary by several orders of magnitude among and within reservoirs.

In this paper, we develop a general analytic model to place bounds on the storage potential and rate at which CO₂ can be sequestered in permeable geologic reservoirs. For this analysis, we use the model to assess the potential of saline aquifers in sandstone sedimentary units, estimating the maximum storage potential and injection rates of these reservoirs as well as the minimum resulting cost per tonne CO₂ of storage. We compare and calibrate our model results with three deep saline aquifer injection pilot projects: Nagaoka, Japan, the Frio formation in Texas, and the Norway’s Sleipner West field in the North Sea. Finally, we apply the model to estimate a range of geosequestration costs for a group of sedimentary basins throughout the United States.

2.2. Analytical Model

The elements of geosequestration addressed by our model are depicted schematically in Fig. 3. In the model, we assume that the CO₂ to be injected underground is already in a supercritical state, having a temperature, pressure, and density of \( T_{\text{crit}} \), \( P_{\text{crit}} \), and \( \rho_{\text{crit}} \) respectively. In our application of the model, this CO₂ is piped down a well into a tabular sandstone saline reservoir of thickness \( b \) (meters)
sealed above and below by impermeable strata. The model developed to analyze this system has three components, explained in the following sections.

2.2.1 Component 1: Maximum CO₂ Storage Potential

The CO₂ storage potential of a saline reservoir varies with depth in at least three ways. As reservoir depth increases, pressure increases, increasing CO₂ density and thus the effective storage potential of the reservoir. However, temperature also increases
with depth, reducing density, and as overburden pressure increases, reservoir porosity is reduced, causing an offsetting reduction in effective storage potential (Athy 1930).

We model these changes over a range of depths. Temperature and pressure are used to determine the density of the sequestered supercritical CO$_2$, while the available void space to be occupied by this fluid depends on porosity.

We use a linear approximation of the relationship between temperature and depth (Turcotte & Schubert 2002), i.e.

$$T(z) = T_0 + c_1 z. \quad [1]$$

Here, $T_0$ is temperature at the surface, $c_1$ is the temperature gradient, and $z$ is depth.

We also model the relationship between pressure and depth as linear under hydrostatic conditions. The relationship can be expressed as

$$P(z) = \rho_w g (z - z_0) \quad [2]$$

where $\rho_w$ is the density of the fluid column, $g$ is the acceleration of gravity and $z_0$ is the depth of the water table (Freeze & Cherry 1979). Note that as salinity and thus density of the pore water increases in [2], so does pressure.

Porosity decreases with depth at an exponential rate, defined by Athy’s Law (Athy 1930),

$$\phi(z) = \phi_0 e^{-c_3 z} \quad [3]$$

where $\phi_0$ is porosity at the surface and $c_3$ is an empirically determined constant.

As with temperature and pressure, porosity varies considerably in strata even at a particular depth. However, while local variation in porosity will change the magnitude of the storage potential function, it will not significantly change the function’s shape, as the gradient depends on overburden pressure.
Finally, we use the standard Boyle’s and Charles’ Laws for gases to account for changes in the density of the supercritical \( \text{CO}_2 \) fluid as it enters different temperature and/or pressure zones in the reservoir. Although these laws do not hold over the nonlinear transition to supercritical state (Stefan Bachu 2003), the behavior of supercritical fluid is essentially that of an ideal gas under most of the temperature and pressure regimes considered; in deeper reservoirs, this approximation will overestimate density. Effective storage is further constrained by available void space. Together, the model combines these laws with Equation [3] to arrive at the following equation for maximum effective storage potential (\( V_e \), e.g. measured on a volume \( \text{CO}_2 \) per volume reservoir basis) at a given depth:

\[
V_e = \frac{T_{\text{crit}}}{P_{\text{crit}}} \cdot \frac{P(z)}{T(z)} \cdot \phi(z)
\]  \[4\]

Equation [4] is the maximum effective storage potential of the void space in the rock irrespective of the temporal evolution of the \( \text{CO}_2 \) plume if the total pore volume is filled solely with \( \text{CO}_2 \) only (a condition which is unlikely to occur in most of the bulk volume of the reservoir (IPCC 2005)).

### 2.2.2 Component 2: Maximum \( \text{CO}_2 \) Injection Rate

The maximum rate at which \( \text{CO}_2 \) can be discharged into a reservoir is limited in theory by the injection-induced pressure that would cause hydraulic fracturing beyond the perforated zone around the well. Hydraulic fracturing is dictated by the difference between the overburden stresses compressing the rock matrix together and the fluid pressure from within the pores pushing out on the matrix as it is being squeezed. Hydraulic fracture occurs when the pore pressure is high enough that the state of effective stress, i.e.
\[
\sigma_n = \left( \frac{\sigma_1 + \sigma_3 - P_f}{2} \right) + \left( \frac{\sigma_1 - (\sigma_3 - P_f)}{2} \right) \cos(2\theta) \tag{5}
\]

\[
\sigma_T = \left( \frac{\sigma_1 - (\sigma_3 - P_f)}{2} \right) \sin(2\theta) \tag{6}
\]

for any plane of fracture (defined by the angle \( \theta \)) reaches the Mohr-Coulomb failure criterion

\[
\sigma_T = \tau_s + \sigma_n \mu . \tag{7}
\]

In these equations, \( \sigma_n \) is the normal stress due to overburden pressure \( \sigma_i \) and the tensional stress \( \sigma_T \), which includes both hydrostatic pressure (\( \sigma_1 \)) and any additional pore pressure due to injection (\( P_f \)). \( \tau_s \) is the shear strength of the rock matrix and \( \mu \) is the friction coefficient, both of which are empirically determined constants(Suppe 1985).

Our model solves equations [5]-[7] for \( P_f \), which is the maximum overpressure the reservoir can bear before fracturing. The pressure is converted to a volumetric rate from the injection well using a solution of Darcy’s law known as the Theis well function(Freeze & Cherry 1979).

\[
X = Kb \tag{8}
\]

\[
S = S_s b \tag{9}
\]

\[
S_s = \rho_w g (\alpha + \phi(z)\beta) \tag{10}
\]

\[
u = \frac{S}{4X} f \tag{11}
\]

\[
Q_{vol} = -P_f 4\pi X \frac{g \rho E_i(u)}{\rho E_i(u)} . \tag{12}
\]
Equation [8] determines the transmissivity ($X$) of the reservoir as a function of hydraulic conductivity ($K$) and layer thickness ($b$). Equation [9] determines the storativity ($S$) of the reservoir as a function of the specific storativity of the material composing the reservoir ($S_s$) and its thickness ($b$), where specific storativity is calculated with Equation [10] (storativity is not related to effective storage potential). Equation [10] shows that specific storativity is a function of the density of water and the acceleration of gravity, the compressibility of the rock skeleton ($\alpha$), the porosity of the reservoir ($\phi$), and the compressibility of water ($\beta$) (Freeze & Cherry 1979).

The Theis well function in Equation [12] relates volumetric flux to the pressure differential ($P_f$) between two locations (in this case the well and the background pressure of the reservoir) as well as parameters from Equations [8]-[11]. $f$ in Equation [11] describes the zone of influence in which fracture is permitted spatially and temporally (Freeze & Cherry 1979).

Equation [12] uses the pressure ($P_f$) from Equations [5]-[7] to determine the maximum rate at which a fluid can be injected before major fracturing of the reservoir rock will occur. We calculate an approximate absolute permeability using

$$k = \sqrt{k_hk_v}$$

where the vertical permeability ($k_v$) is 0.3 times the horizontal permeability ($k_h$) for anisotropic reservoirs, although this ratio of vertical to horizontal permeability can vary among anisotropic reservoirs (Law D.H. & Bachu S. 1996). Permeability is converted to hydraulic conductivity ($K$) for Equation [8] (Freeze & Cherry 1979). Equation [12] is not modified for two-phase flow, so viscosity, miscibility, and buoyancy are not taken into account. These factors should most affect viscous fingering, dissolution, and vertical plume evolution, however, and in this type of flow,
compressibility along the flow path will be negligible (Wiggert & Potter 2002). In thick layers, the density of the gas in the fluid column relative to the reservoir pore fluid means that the pressure differential between the injection well and the reservoir pore pressure over the layer is not constant. A correction factor is applied to account for this when necessary.

Finally, the results of Equation [12] are converted to a mass rate. This is accomplished using the local temperature and pressure to compute the corresponding local supercritical fluid density, i.e.

$$Q_{mass} = \rho_{crit} \frac{T_{crit}}{P_{crit}} \frac{P(z)}{T(z)} Q_{vol}$$  \[14\]

2.2.3 Component 3: Cost per Tonne of CO_2 Geosequestration

The last component of our model is an economic analysis of the cost of injection in terms of cost per emissions stored. We construct a relationship between the total cost of a geosequestration project and the emissions stored to arrive at a cost per tonne of CO_2. We estimate the capital cost and operations and maintenance (O&M) cost of these wells amortized over a project lifetime to compute total costs. Note that a distinction arises between emissions “stored” and “avoided” because there is an energy penalty to capturing and transporting the CO_2 to the injection site. Since the entire CCS system must be evaluated to consider emissions avoided rather than emissions stored (IPCC 2005), we evaluate the geosequestration component with a cost per emissions stored to permit integration with different capture technologies or CO_2 transport requirements.

We determine average cost for sequestration on a single-well basis (rather than a firm-level cost estimate, since variables such as emissions rates are essentially arbitrary unless studies of specific firms are undertaken). Total costs are assumed to be a
combination of drilling, injection equipment, and O&M costs. Drilling and injection equipment costs increase nonlinearly with depth, as given by the quadratic functions

\[ C_{\text{drill}} = a_1 + b_1z + c_1z^2 \quad [15] \]

\[ C_{\text{inj}} = a_2 + b_2z + c_2z^2 \quad [16] \]

where the coefficients are estimated by statistical methods from the available data. In our application, we find that a quadratic function fits the data better over the depth range of interest compared to an exponential function, as discussed in the next section. The model annualizes these up-front fixed costs using amortization factor \( A \), which is a function of the discount rate \( r \) and the project lifetime \( t \)

\[ A = \left( 1 - \frac{1}{(1 + r)^t} \right)^{-1}. \quad [17] \]

Annual O&M costs are assumed to be 10% of fixed annual costs based on Bock (Bock 2002), implying that the full average cost function is given by

\[ AC = \frac{1.1A(r,t)(C_{\text{drill}}(z) + C_{\text{inj}}(z))}{Q_{\text{max}}} . \quad [18] \]

Note that this estimate may be optimistic, since maintaining higher pressures for higher injection rates will presumably lead to higher O&M costs.

### 2.3. Application

We apply our model to deep saline aquifers in sandstone reservoirs. We evaluate maximum effective storage potential and injection rate as a function of depth between two end-member cases for a base case set of reservoir properties. The lower end-member corresponds to reservoir properties leading to higher costs. (For a full explanation of parameters, see Appendix A.) We limit our model to a subsurface depth
range of between 500 - 3000 m. This range encompasses the shallowest depth at which CO$_2$ is supercritical and the average maximum depth of sedimentary basins in the United States (Bureau of Economic Geology (BEG) 2000). Below this depth, effective storage is constantly decreasing and cost per tonne of injection is constantly increasing.

To evaluate the end members for conditions found in sandstone reservoirs, we consider two profiles for temperature and pore fluid density ([Nordbotten et al. 2005; U.S. Geological Survey 1995]; Appendix A for details). The high temperature and low fluid density profiles (associated with basin geothermal properties and dissolved solids in pore fluid, respectively) form the constraints for the lower end member and the low temperature and high fluid density profiles form the constraints for the upper end member.

We first solve for the effective storage potential given by [4]. Upper and lower end members for temperature and pressure as well as the porosity curve are the inputs to this equation and are computed as functions of depth using Equations [1]-[3]. We determine maximum injection rate by first solving Equations [5]-[7] for the maximum injection well pressure, and then use this in Equation [14] along with the other inputs from Equations [8]-[13] to compute the range of theoretical maximum injection rates. We use parameters from literature (Turcotte & Schubert 2002; Suppe 1985; Bahr et al. 2001; Fetter 2001); see Appendix A) for a base-case reservoir having a thickness of 65m and a permeability of 22 md. These last two values are based on a compilation of sedimentary basin measurements in the U.S. assembled by the Texas Bureau of Economic Geology (BEG)(2000). We calculate an average (area-weighted) reservoir depth of 1350 meters, an average net sand thickness of 65 meters, and a log-averaged
permeability of 22 md (however, note that permeability ranges over several orders of magnitude).

The zone of influence term \((f)\) is based on the maximum injection rate which would lead to hydraulic fracturing as reported for the Nagaoka site, which is 48 t/day (Research Institute of Innovative Technology for the Earth (RITE) 2007). This estimate yields a value of 0.02 for \(f\). We place the lower boundary for injection rate slightly above this in order to make the model more conservative.

Finally, we determine the cost per tonne of CO\(_2\) sequestered in 2005 dollars as a function of depth from the injection rate. The total capital costs in Equation [18] are a combination of drilling costs (Equation [15]) and injection costs (Equation [16]). We estimate the coefficients of Equation [15] using a quadratic regression on data from the Joint Association Survey on Drilling Costs from 2003 (Augustine et al. 2006), adjusted for increases in drilling costs to 2005 dollars (EIA 2007). We estimate the coefficients of Equation [16] using a quadratic regression on data from the Energy Information Agency (EIA) on injection equipment costs for Enhanced Oil Recovery (EOR) (EIA 2007), in which we do not include the potential cost of additional compression equipment at the injection site. We calculate an amortization factor to convert this capital cost into the levelized annual cost of this equipment incorporating the discount rate used by the EIA for electricity market modeling of 11.55\%(EIA 2007) over a project lifetime of 20 years (used by the Electric Power Research Institute in evaluating CCS) (Bock 2002) in Equation [17]. Note that the final cost of storage can be highly sensitive to these assumptions; using a discount rate of 10\% over a project lifetime of 25 years, for example, would reduce the amortization factor by 15\%. We then calculate cost per tonne
using the upper and lower bounds on the range of maximum injection rates (per year) with Equation [18].

2.4. Results

2.4.1 CO₂ Storage Potential

According to our model, 0.33-0.66 m³ of CO₂ at surface supercritical conditions (or 0.18-0.31 tonnes) can be sequestered per cubic meter of reservoir rock in sandstone reservoirs (Fig. 4a). Storage varies with depth by approximately the same magnitude as it does between the end members, indicating that at a single spot in a basin there is as much variation with depth as there is among basins at any given depth. The model also shows that the depth at which effective storage potential is optimal is ~1600 meters, at which point effective storage ranges between 0.45 and 0.66.

Our result differs markedly from previous studies (IPCC 2005). While those earlier studies tend to show potential storage increasing monotonically with depth, our model predicts that storage rises to a maximum at intermediate depths and then declines. This behavior arises from non-linear changes in porosity and from accounting for the counteracting effects of temperature and pressure on fluid density with depth. Note that changes in temperature and pressure lead to slight changes in exactly where the maximum storage occurs (on the order of 100 meters) but produce significant changes in the actual magnitude of storage potential.
Figure 4: Model Results. This figure shows the range of effective storage as a function of depth, measured as the volume of CO₂ under surface supercritical conditions that would occupy the entire pore space of a cubic meter of reservoir volume (2a), the range of theoretical maximum injection rates in the base-case reservoir permeability and layer thickness (2b), and resulting cost per tonne of CO₂ avoided as a function of depth (2c), with an optimal depth near 1300 meters. The low end-member corresponds to high temperatures and low pore fluid density, and the high end member to low temperatures and high density.

To put this result in context, a minimum of approximately 0.7 km³ of reservoir volume at the optimal depth would be required to store the emissions from a typical 500 MW coal plant capturing 7389 tonnes of CO₂ per day for 20 years with an 80% capacity factor\(^{(\text{Bock 2002})}\). Note that this is the minimum amount of physical space (i.e. reservoir
volume) necessary for storing the CO$_2$. Numerical simulations and pilot projects have indicated that CO$_2$ plume evolution often bypasses the vast majority of this available space. For example, numerical simulations of the Frio injection project have assumed that between 5% and 30% of pore space will be occupied (Hovorka et al. 2001). If correct, the volume necessary to sequester CO$_2$ will be three to twenty times higher than the minimum predicted by our model.

2.4.2 Maximum CO$_2$ Injection Rate

In terms of thresholds for maximum injection rates, the model predicts that at the average reservoir depth of 1350 m, 50-80 t CO$_2$/day could be injected (See Fig 4b). The maximum injection rate increases with depth for two major reasons. First, as depth increases, the threshold pressure for hydraulic fracturing increases, allowing for higher injection well pressures. Second, the density of supercritical CO$_2$ increases with depth, meaning that even constant volumetric flux would lead to higher injection rates at deeper injection depths.

Calibration and comparison of the model results with the Nagaoka, Japan project and two other projects that have published rates of CO$_2$ injection in deep saline aquifers shows that the lower injection rate seems more reasonable (see Fig 5a-c). As noted previously, only the Nagaoka project has explicitly stated the injection rate that would cause hydraulic fracturing (48 t CO$_2$/day (19), Figure 5b). The other two projects cite only actual or designed injection rates, both of which fall below the lower injection rate predicted by our model (E. H. Perkins 2003; Research Institute of Innovative Technology for the Earth (RITE) 2007; Hovorka et al. 2001). That the actual injection rate is below the range predicted by the model may reflect the fact that engineering constraints (e.g. the maximum rate that CO$_2$ can actually be pumped into the well by compressors) and
actual reservoir conditions require lower injection rates than the theoretical limits predicted by the model.

Figure 5: Comparison of Pilot Projects, our Model Results, and Bock’s Calculations. This figure shows model runs using permeability and layer thickness values from each project. The reported values of those projects or models are shown in red.

2.4.3 Cost per Tonne of CO$_2$ Geosequestration

Our model indicates that the cost of geosequestration is substantial, approximately $3.50 per tonne of stored CO$_2$ at the optimal depth (for the model results
most closely matching pilot projects). The model predicts $2-7/\text{tonne}$ for the full range of depth and basin characteristics for the base case permeability and layer thickness (although costs continue to increase at depths greater than 3000m), with an optimum depth near 1300 meters. This cost per tonne of CO$_2$ stored reflects the injection rate (Fig 4b) and the total cost of injection over the modeled project lifetime, shown in Fig 2c. Recall that we calculate these costs assuming the maximum possible injection rate and storage, meaning that these are minimum theoretical costs.

Lower injection rates at shallower depths mean lower amounts of CO$_2$ stored, so as the amount of CO$_2$ stored increases with depth, cost per tonne decreases. However, because the cost of drilling and injection equipment increases in a nonlinear fashion with depth, the decrease in cost gradually peaks at close to 1300 m in both the upper and lower end member cases and cost per tonne begins to increase monotonically with depth beyond that point.

When we apply the model using the mean depth, layer thickness, and permeability of candidate reservoirs around the United States, we arrive at a much wider variation in the cost of sequestration than our base case, as shown in Figure 6. The figure shows that cost sensitivity to reservoir depth is relatively minor, affecting cost by a factor of up to two. Layer thickness and permeability, however, can potentially increase cost by a factor of 50 when decreased to their lowest limit. Close to the upper limit of permeability, storage costs are pennies per tonne, but it is important to note that increasing layer thickness has diminishing returns beyond approximately 1000 m due to the nonlinear term in drilling costs. This indicates that the two factors that have the greatest effect on cost are permeability and layer thickness. All told, cost per tonne ranges over almost four orders of magnitude for the full range of reservoir
characteristics, and these effects compound one another, so real cost will vary over an even wider range.

Figure 6: Sensitivity Analysis: Cost as a Function of Basin Parameters. Along the x-axis, 0 corresponds to the non-dimensionalized base case values for the reservoir characteristics while minimum and maximum values are scaled to –1 and 1, respectively. The mean properties of each of the 21 basins from the Texas Bureau of Economic Geology are plotted on this sensitivity analysis, showing that mean properties can and do vary over the whole range considered. Finally, the three panels below this graph show how these properties vary within and among basins. The squares in the top figure correspond to the circles in the bottom three figures. See supporting information to convert raw parameter values to figure values.
The range of properties in natural basins actually does vary across the range considered in the sensitivity analysis and in many cases even beyond the extremes, indicating actual costs will similarly vary (See Fig. 6). The effect of the distribution of these values on storage cost is shown in Figure 7, which depicts each reservoir evaluated and the maximum, average, and minimum cost per tonne for that reservoir. Although the model does not determine whether the factors that would produce these cost estimates occur in the same places, it is a reasonable conclusion that costs even within a single basin will vary from being very inexpensive to prohibitively costly.

Figure 7: Basin Average, Minimum, and Maximum Cost per Tonne of CO₂ Stored. The model results for the combination of mean depth to formation, net sand thickness, and permeability parameters in each basin are shown in the large map. The parameter combinations that yield the lowest cost and highest cost are shown in
the smaller maps. Note this analysis does not consider the spatial distribution of reservoir characteristics; therefore it does not assess total effective storage at any cost level in these basins.

2.5. Discussion

The extreme variability in aquifer characteristics means that cost estimates for geosequestration will vary widely around our base case figure for minimum theoretical costs of ~$3.50/tonne. As noted above, we conclude that it is virtually certain that there are regions in many reservoirs with extremely low injection costs per tonne of CO$_2$ sequestered. The most important conclusion of this analysis, however, is that the quantity of storage that could be provided in the low cost regions is likely to be much lower than the thousands of gigatonnes often cited as the potential storage capacity of deep saline aquifers (IPCC 2005).

This conclusion arises because the sensitivity analysis shows that there are quite a few regions of major reservoirs that have neither ideal permeability nor ideal layer thickness, leading to higher storage costs than previously projected. Creative engineering such as long-reach horizontal drilling may solve some of these problems, but the cost sensitivity analysis shows the potential limits of that solution; the reduction in cost from effectively extending layer thickness through horizontal drilling to thousands of meters provides diminishing returns due to the higher cost of deeper or nonvertical, longer wells. Since our analysis is performed on a single-well basis, though, we do not account for possible economies of scale in a multi-well system. However, we also do not account for possible interference between wells in a multi-well system, both of which might affect the economics significantly.

Nonetheless, we can conclude that some tracts of sedimentary basins tentatively identified as having considerable storage potential are unlikely to prove economically
viable unless carbon prices support geosequestration storage costs (not including capture and transport) near $20 per tonne of CO$_2$. It is important to note, however, that these analyses give general estimates for costs of geosequestration, and cannot be used as substitutes for a full simulation of a specific site.

Overall, the economics of carbon sequestration depend on many separate cost components, including capture, transport, sequestration, and monitoring. Among those, geosequestration has previously been estimated to be a very minor component of the full cost of CCS. For example, to date, the most comprehensive analysis of geosequestration options in the United States is a report by Bock for the Electric Power Research Institute (EPRI)(2002). Bock used a base-case reservoir similar to ours (based on the same BEG data) of 171 m thickness, 22 md permeability, and 1240 m depth(2002). The layer thickness, for example, is different because his determination of layer thickness relied on a simple average of formation thickness, not an aquifer size-weighted average of net sand thickness.

More importantly, Bock’s report predicts that only one well would be required to inject an average coal plant’s output (almost 10,000 tonnes of CO$_2$ per day). This prediction is based on a calculation from a formula derived by Law and Bachu(1996) that relates injection well pressure directly to injection rate. The formula was derived from a regression on a series of results from a numerical simulation designed to estimate the effect of local “sweet spots” on injection rates, not a general rule for relating injection pressure directly to injection rates. The outcome of this simplification is that injection rates calculated by Bock are three times higher than those achieved at Sleipner West, where permeability is 100 times greater than the value used in Bock’s calculations(E. H. Perkins 2003). With Bock’s injection rates, large-scale hydraulic fracturing would result,
as shown in Figure 5, which plots actual injection rates at the three pilot projects versus that predicted by Bock. This result suggests that the cost estimates in Bock are too optimistic. The average costs for injection into an aquifer are likely to be over ten times higher than Bock’s estimate of approximately $0.30 per tonne (2002).

Additionally, realistic engineering constraints make injection at very high overpressures unlikely. This is reflected in Figure 5, which indicates that design capacities for injection rates at existing pilot projects are well below the range of theoretical maximum rates predicted by our model. One implication of this conclusion is that the assumption that O&M costs are a fixed percentage of capital cost is also overly optimistic. These costs will increase as the injection rate increases. Either O&M costs will need to be reduced by drilling more wells to achieve the same injection rates (increasing capital cost), or higher O&M costs will arise from having to maintain impractically high injection rates.

In summary, attractive geosequestration opportunities are likely available depending on key characteristics such as high average permeability and thick layers at depths conducive to maintaining carbon dioxide in a supercritical state at optimal storage and injection rates. However, these characteristics can vary widely enough to make geosequestration unattractive in many areas of sedimentary basins, changing the nature of the available supply of carbon storage reservoirs in the United States. The focus of our future work will be to identify the portions of specific reservoirs where costs will be lowest and to estimate the storage capacity and geosequestration supply curves at these locations.
3. Geospatial Distribution of Sequestration Potential in the United States

3.1. Introduction

The Intergovernmental Panel on Climate Change (IPCC) projects that to stabilize the atmospheric CO₂ concentration between 440-485 ppm, global CO₂ emissions must peak between 2010 and 2030 and decrease soon thereafter (Bernstein et al. 2007). Energy use is the major contributor to greenhouse gas (GHG) emissions, and although conservation and low-carbon technologies can help reduce emissions, demand for fossil fuels such as coal is increasing (Bernstein et al. 2007). One way that fossil fuel use could continue while constraining GHG emissions is through the implementation of geologic carbon capture and storage (CCS) (Hoffert et al. 2002; Pacala & Socolow 2004; IPCC 2005), i.e. capturing CO₂ emissions at major industrial point sources, such as power plants, and transporting the CO₂ via pipeline to sites where the GHG would be injected underground into geologic reservoirs for long-term storage.

As a mitigation strategy, CCS will likely see broad-scale deployment only if large quantities of CO₂ can be captured and stored relatively cheaply. The most promising geologic sink for CO₂ is saline aquifers. These appear to have tens to hundreds of times the storage potential of other possible onshore CO₂ sinks, including coal seams, basalts, and oil and gas reservoirs (IPCC 2005). How much CO₂ can actually be sequestered in saline aquifers has been the subject of a number of studies, as well as a focus of major U.S. and international collaborative research programs (e.g., the U.S. Department of Energy (DOE) National Carbon Sequestration Database and Geographic Information System (NATCARB) and the International Energy Agency Greenhouse Gas R&D
Programme (IEAGHG)). The capacity estimates produced by these and other studies vary considerably (Stefan Bachu et al. 2007), but first-order assessments at the global scale (Koide et al. 1992) through more detailed assessments at the continental to national level (e.g., the Indian sub-continent by Holloway et al. (2009) and the USDOE Sequestration Atlas for North America (Department of Energy (DOE) 2010)) repeatedly demonstrate that deep-saline aquifers could store up to centuries worth of current anthropogenic CO₂ emissions.

Less clear is the likely cost of this form of storage. Analyses for the United States (Bock 2002), Europe (Hendriks et al. 2004), and Australia (W. G. Allinson et al. 2003) initially suggested storage costs in saline aquifers might be $0.5-$3/tonne (IPCC 2005). Subsequent work, however, has projected costs that are higher and/or more variable (BCG 2008; McKinsey Climate Change Initiative 2008; Al-Juaied & Whitmore 2009; Eccles et al. 2009; Dooley et al. 2008). Variability in storage costs is important because it can significantly affect transport costs for CCS. To optimize the overall cost efficiency of a CCS system, transport costs must be traded off against storage costs in such a way as to minimize their combined expense. This makes accurate information about storage costs critical.

The value of integrating transport and storage in cost assessments has been demonstrated by efforts ranging from the IEA GHG Programme (Wildenborg et al. 2004) to the SimCCS modeling package developed by Middleton and Bielicki (2009). The integration is achieved by using a transport optimization algorithm to link each CO₂ point source in a region to a potential storage reservoir. The total cost of transport and storage is then computed weighted by each firm’s emissions. Integrated assessments have produced marginal abatement cost curves (MACCs) for CO₂ transport and storage
from major point sources in North America (Dooley et al. 2004), Europe (Wildenborg et al. 2004), and China (Dahowski et al. 2009). The curves are built by adding the potential abatement of emissions from each point source to the abatement potential of the other sources in order of increasing cost of transport and storage per tonne of CO₂.

Developers of the MACCs acknowledge that the geologic heterogeneity of saline aquifers could lead to storage cost estimates that range over several orders of magnitude (Dooley et al. 2004). However, due to lack of data and/or methods for adequately incorporating heterogeneity in reservoir quality, existing MACCs are based on an average or even single estimate of storage capacity and cost per aquifer (Middleton & Bielicki 2009; Wildenborg et al. 2004); and in some cases the constant values are applied to all the aquifers evaluated (Dooley et al. 2004; Dahowski et al. 2009). Thus cost variations in the MACCs are predominantly the result of varying transport distances between the CO₂ point sources and saline aquifers, and do not reflect potential additional variability due to storage.

The assumption that storage capacity and cost is constant within and even among reservoirs is suitable if the reservoirs are small, well-defined and can be adequately characterized by summary statistics, as is the case for many oil and gas fields. However, deep saline aquifers are large, and spatial variations in their reservoir properties can be significant, leading in turn to significant variations in storage costs. We illustrate that these variations are not adequately represented by single or even average capacity and cost estimates by using a publically available dataset that includes extensive and detailed information on key reservoir properties for 15 deep-saline sandstone aquifers in the United States. We rasterize these data where they are dense enough and then input the rasters into our previously published model (Eccles et al., 2009).
(2009) to produce corresponding rasters of estimated storage capacity and cost. We then use these rasters to build purely storage-based MACCs, which do not include transport costs from existing CO₂ point sources and only describe the resource potential of the aquifers. The rasters and MACCs are not comprehensive assessments of U.S. storage potential, but are inclusive enough to show that estimated storage capacities and costs are not uniformly distributed spatially nor normally distributed statistically. This means that the use of average capacity and cost estimates for entire saline aquifers can grossly misrepresent the true capacity and cost for CO₂ storage at many sites within the aquifers. The MACCs also reveal an inverse relationship between estimated storage capacity and cost, one in which the regions analyzed are dominated by relatively high capacity, low cost storage sites. This relationship is not so much tied to the surface area of the aquifers as it is to their thickness. Further development of spatially-based storage capacity and cost estimates is needed if transport optimization algorithms are to be used to map out cost-effective configurations for potential pipeline routes connecting CO₂ sources to these aquifers and similarly large candidate reservoirs.

3.2. Methods

3.2.1 Data

Our approach to constructing storage-based MACCs involves using geospatially referenced reservoir properties that can be rasterized to represent the aquifers as large, continuous underground entities. This requires that the geologic property data are (1) extensive and dense enough to reveal systematic variations within the aquifer at scales descending to the cell size of the rasters, and (2) that the data include parameters from which storage capacity and cost can be determined. These are particularly challenging
requirements for deep saline aquifers, as they are not as well characterized as oil and gas reservoirs (Stefan Bachu et al. 2007). Publically available GIS data from the NATCARB project was, for example, not adequate for our approach because it satisfied neither requirement. In NATCARB, deep-saline aquifers as well as other candidate reservoirs with spatial extents >100,000 km$^2$ are represented as homogeneous bodies and are summarized only by total storage capacity (Department of Energy (DOE) 2010). The data on which the capacity estimates are based can be extensive (Department of Energy (DOE) 2010) but never include permeability and often lack other similarly critical parameters we need to determine cost using our previously published model (Eccles et al. 2009).

Instead, we use data compiled, digitized and made publically available by the Texas Bureau of Economic Geology (BEG) for 15 deep-saline sandstone aquifers located around the United States. These aquifers, outlined in blue in Figure 8, represent some of the nation’s largest sequestration opportunities (Bureau of Economic Geology (BEG) 2000). The aquifers are indexed to Table 1, which identifies the aquifers in terms of the basin in which they are located, the stratigraphic formation or group in which they occur, the total surface area of the aquifer, and how much this area we were able to rasterize.
Figure 8: Spatial Distribution of Geosequestration Quantity and Cost. (A) Quantity of storage in tonnes per square kilometer and (B) Distribution of cost in BEG Study Areas. The basin areas that may have storage potential but lacked sufficient data to analyze are shown in blue. Gray areas are regions where cap depth is too shallow. Although the Mt. Simon extends further than indicated on the map, our analysis only included geological data characteristic of the Michigan area.

The BEG data for the aquifers include eight key reservoir properties needed by our capacity/cost model; formation depth, permeability, net sand thickness, formation thickness, temperature, pressure, salinity, and porosity. These data are in various digital formats (see Table B1 in Appendix B), all of which have been converted into rasters with grid cell sizes of 1km x 1km. For the most part, the BEG data are isolines, which we rasterized using the ESRI ArcGIS topo-to-raster tool. Data files that were in point form were rasterized by kriging. If an aquifer was represented as a polygon, we converted it directly into a raster with cell values equal to the value assigned to the polygon. Several of the eight key parameters needed by our model to estimate potential storage capacity and cost were commonly missing from the database, primarily temperature, pressure, and/or porosity. We were able to reconstruct these from other information, such as depth by using published gradients for temperature, pressure, and porosity (Bahr et al. 2001; Eccles et al. 2009; Nordbotten et al. 2005).

Since our method relies on interpolation, which is limited by the maximum spatial extent of the input data, we were only able to produce partial rasters of each key parameter in each sandstone saline aquifer. Furthermore, we could only model storage capacity and cost in an aquifer where the rasters of all eight key parameters overlapped. These correspond to the grey and/or colored regions that lie inside the blue outlines of the aquifers in Figure 8. As a result, our capacity and cost estimates extend over only 30% of the roughly 700,000 km² of surface area for all the aquifers.

Table 1: List of Analyzed Formations and Map Indices
Table 1: List of Analyzed Formations and Map Indices

<table>
<thead>
<tr>
<th>Basin</th>
<th>Formation</th>
<th>Surface Area (km²)</th>
<th>Data Coverage</th>
<th>Data Coverage (km²)</th>
<th>Map Index</th>
</tr>
</thead>
<tbody>
<tr>
<td>Los Angeles Basin</td>
<td>Repetto Formation</td>
<td>15,600</td>
<td>13%</td>
<td>2,028</td>
<td>1</td>
</tr>
<tr>
<td>Sevier Basin</td>
<td>Glen Canyon Group</td>
<td>371,000</td>
<td>29%</td>
<td>107,590</td>
<td>2</td>
</tr>
<tr>
<td>San Juan Basin</td>
<td>Morrison Formation</td>
<td>49,600</td>
<td>6%</td>
<td>2,976</td>
<td>3</td>
</tr>
<tr>
<td>Powder River Basin</td>
<td>Fox Hills/Lower Hell Creek</td>
<td>69,000</td>
<td>19%</td>
<td>13,110</td>
<td>4</td>
</tr>
<tr>
<td>Denver Basin</td>
<td>Lyons Sandstone</td>
<td>170,000</td>
<td>38%</td>
<td>64,600</td>
<td>5</td>
</tr>
<tr>
<td>Palo Duro Basin</td>
<td>Granite Wash</td>
<td>63,800</td>
<td>39%</td>
<td>24,882</td>
<td>6</td>
</tr>
<tr>
<td>Texas Gulf Coast</td>
<td>Frio Formation</td>
<td>138,600</td>
<td>76%</td>
<td>105,336</td>
<td>7</td>
</tr>
<tr>
<td>East Texas Basin</td>
<td>Woodbine Formation</td>
<td>97,500</td>
<td>42%</td>
<td>40,950</td>
<td>8</td>
</tr>
<tr>
<td>East Texas Basin</td>
<td>Paluxy Sandstone</td>
<td>101,300</td>
<td>7%</td>
<td>7,091</td>
<td>9</td>
</tr>
<tr>
<td>Illinois Basin</td>
<td>St. Peter Sandstone</td>
<td>568,800</td>
<td>26%</td>
<td>147,888</td>
<td>10</td>
</tr>
<tr>
<td>Black Warrior Basin</td>
<td>Pottsville Formation</td>
<td>24,900</td>
<td>10%</td>
<td>2,490</td>
<td>11</td>
</tr>
<tr>
<td>Michigan</td>
<td>Mt. Simon Formation</td>
<td>164,000</td>
<td>25%</td>
<td>41,000</td>
<td>12</td>
</tr>
<tr>
<td>Appalachian Basin</td>
<td>Oriskany Formation</td>
<td>358,000</td>
<td>42%</td>
<td>150,360</td>
<td>13</td>
</tr>
<tr>
<td>South Carolina Coastal Plain</td>
<td>Cape Fear Formation</td>
<td>91,700</td>
<td>25%</td>
<td>22,925</td>
<td>14</td>
</tr>
<tr>
<td>Eastern Coastal Plain</td>
<td>Lower Potomac Group</td>
<td>106,600</td>
<td>6%</td>
<td>6,396</td>
<td>15</td>
</tr>
<tr>
<td>Alabama Gulf Costal Plain (missing data)</td>
<td>Tuscaloosa Group</td>
<td></td>
<td></td>
<td></td>
<td>16</td>
</tr>
</tbody>
</table>

Note that we restricted our evaluation to sandstone aquifers since our model for estimating storage capacities and costs was developed and calibrated using sandstone injection projects (Eccles et al. 2009). Furthermore, we depict the aquifer as a single layer. In reality, the formations or groups containing the aquifers are multilayered, and in general only the sandy layers with sufficient porosity and permeability serve as part of
the aquifer, since muddy layers are too impermeable. The BEG data are not detailed enough to separate out the sandy and muddy layers, so we use the net sand thickness of the formation/group as the “effective” thickness of the aquifer, i.e. the thickness in which CO$_2$ can be stored.

For these and other reasons, our study is not a comprehensive assessment of the potential capacity and cost for storing CO$_2$ in U.S. deep saline aquifers. Instead it is an analysis of how storage capacity and cost can vary across such aquifers as revealed by our mapping method. For a complete explanation of our interpolation and reconstruction methods for each study area, see Appendix B Section B1.

### 3.2.2 Model

We apply our previously published model (Eccles et al. 2009) to each grid cell in the rasterized regions in Figure 8 to produce corresponding capacity and cost rasters from which we can then build a storage-based MACC. Our model consists of modules for estimating (i) the bulk CO$_2$ storage capacity of deep-saline sandstone aquifers, (ii) the maximum rate at which CO$_2$ can be injected into the aquifers, and (iii) the total cost of carrying out this form of storage. We have updated the model in this study to include several more realistic assumptions for estimating capacities and costs.

#### 3.2.2.1 Capacity Module

The capacity module, like that in Eccles et al (2009), is a relatively simple bulk volume calculation, derived from Bachu et al (2007). The capacity for a given cell is represented by
where $A$ is the storage density of CO$_2$ (in tonnes per square kilometer), $v$ is the bulk rock volume, $\rho$ is density of CO$_2$ in tonnes per cubic kilometer, $\phi$ is the rock porosity, $\epsilon$ is the capacity factor or sweep efficiency, and $i,j$ represent the geospatial coordinates of the cell. Note that $v$ is a function of net sand thickness $b$ and grid cell size $r$ (1km x 1km), and that $\rho$ is a function of temperature $T$ and pressure $P$.

We have improved this part of the model in the calculation of density and in the use of the capacity factor. For density, we now use the equations of state for CO$_2$ published by Span and Wagner (1996) in place of the ideal gas law used in Eccles et al. (2009). The ideal gas law is sufficient for reservoirs at subsurface depths of <2000-3000 m, but overestimates CO$_2$ density and thus underestimates storage costs in reservoirs that are deeper. The equations of state now provide accurate estimates of CO$_2$ density for reservoirs at all depths.

The other change to this module is the inclusion of the capacity factor in equation [19]. We set this factor to 4% based on computer modeling by Doughty et al (2001) for a saturated homogenous reservoir in which CO$_2$ storage has been maximized. This value is near the upper limit used in NATCARB by the DOE (0.5-5.5%) (2010) but within the range proposed by others (R Burruss et al. 2009; Hovorka et al. 2001). The actual value for capacity factor can be highly site-specific (Stefan Bachu et al. 2007) and, as will be illustrated later, can have a considerable impact on storage capacity estimates (Kopp et al. 2009).

Equation [19] is a relatively simple model for estimating bulk CO$_2$ capacity. It does not include: (i) cap rock integrity, for which additional characterization would be necessary (Stefan Bachu et al. 2007); (ii) pressure constraints, for we assume that the
reservoir will not be overpressurized, which is a conservative assumption (Stefan Bachu et al. 2007; Kopp et al. 2009); or (iii) CO₂ dissolution in the pore water, a relatively small influence during the initial injection period (Doughty et al. 2001)). Nonetheless, this type of equation is considered to be reasonably accurate for regional- to national-scale assessments of the trapping potential of large reservoirs (Stefan Bachu et al. 2007) such as being done here.

3.2.2.2 Injection Module

The rate at which CO₂ can be injected into the aquifer needs to be constrained before the cost of storage can be estimated. The annual injection rate, \( Q_{\text{mass}} \), is a function of several geological properties, such as permeability, layer thickness, and porosity, used to solve the radial integration of Darcy’s law known as the Theis solution, or the well function (Freeze & Cherry 1979):

\[
Q_{\text{mass}} = \rho_{\text{CO}_2} \frac{-P_f 4\pi X}{g \rho_j Ei(u)}
\]  

[20]

This solution is described in detail in Eccles et al (2009) and repeated in Section B2 of Appendix B for the interested reader. The solution yields the maximum injection rate below the threshold pressure at which the reservoir will undergo large-scale fracturing based on its geologic properties. We limit the threshold pressure, \( P_f \), in equation (2) to 90% of the fracturing pressure to account for a safety margin in actual injection projects. We also limit \( Q_{\text{mass}} \) to ≤3,500 tonnes/day, which is the maximum design rate for the well injection pump at the Sleipner CO₂ storage site, an ideal geologic environment for rapidly injecting CO₂ (Eccles et al. 2009). We find that without this limit, certain combinations of geologic properties can lead our model to predict injection rates
that exceed tens of thousands of tonnes per day, which is not yet technologically feasible.

3.2.2.3 Cost Module

The cost module estimates the cost of injection on a per-well basis in dollars per tonne. In our previous study (Eccles et al., 2009), we only considered the cost of drilling and operating the injection well. Here we attempt to include other costs that would be associated with storage, such as site evaluation and monitoring. Our revised cost function is

\[
C_{i,j} = \frac{1.1 \times a_m \times \left( C_{i,j}^{\text{inj}}(z_{i,j}) + C_{i,j}^{\text{drill}}(z_{i,j}) + C_{i,j}^{\text{site}} \right)}{Q_{\text{max}(i,j)}}
\]

where \( C_{i,j} \) is the levelized annual cost for injection per tonne of CO\(_2\), \( a_m \) is an amortization factor, \( C_{i,j}^{\text{inj}} \) and \( C_{i,j}^{\text{drill}} \) are the costs of injection equipment and drilling, both of which are a function of depth \( z \). \( C_{i,j}^{\text{site}} \) is the sum of other costs associated with carrying out the injection, \( n_{i,j}^{\text{wells}} \) is the number of wells needed to achieve the injection rate, and 1.1 is a scaling factor that accounts for annual operations and maintenance (O&M) costs (Eccles et al. 2009), based on early work by Bock (Bock 2002).

\( n_{i,j}^{\text{wells}} \) is determined by taking the annual flux of CO\(_2\) emissions being transported to the storage site (i.e. the raster cell) for sequestration, \( Q_{\text{site}} \), and dividing it by the maximum rate of injection per injection well, \( Q_{\text{mass}} \), determined from equation [20]. Here we assume \( Q_{\text{site}} \) to be 10 Mt/y, or the CO\(_2\) emissions produced annually by
roughly three 500MW coal-fired power plants; sensitivity tests indicate varying site size between 1 and 25 Mt/y does not significantly affect the outcome.

$C_{i,j}^{\text{site}}$ includes the costs for site evaluation (e.g. seismic surveys), monitoring and liability, storage-site distribution pipelines, site remediation, and closing costs. We derive these from a report published by the U.S. Environmental Protection Agency (2008), which attempts to constrain all of the major costs associated with geologic sequestration of CO$_2$. The report subdivides these costs into six major components. One of these is termed injection wells, which includes the costs of drilling the well ($C_{i,j}^{\text{drill}}$, eq. [21]) and carrying out the injection ($C_{i,j}^{\text{inj}}$, eq. [21]). We calculate these specific costs in our model, and so ignore the EPA reported values for them. Each of the remaining component costs is the sum of a series of line-item expenses. These expenses differ from one cost component to the next, and are generally described on a per-unit basis (e.g. $/m$ depth for drilling costs). For the most part, the expenses in all the components can be grouped into five categories: fixed costs ($c_{\text{fixed}}$), costs per unit area ($c_{\text{area}}$), costs per well ($c_{\text{well}}$), costs per unit depth ($c_{\text{depth}}$), and costs per well per unit depth ($c_{\text{well,depth}}$). Each component cost is then arrived at by adding the sum for each expense category after it is converted into US dollars, which is accomplished where necessary by multiplying the category by the appropriate raster variable at the site, i.e.:

$$C_{i,j}^{k} = \sum c_{\text{fixed}}^{k} + \left( \sum c_{\text{area}}^{k} \right) \frac{Q_{i,j}}{A_{i,j}} + \left( \sum c_{\text{well}}^{k} \right) n_{i,j}^{\text{wells}} + \left( \sum c_{\text{depth}}^{k} \right) z_{i,j} + \left( \sum c_{\text{well,depth}}^{k} \right) n_{i,j}^{\text{wells}} z_{i,j} \quad [22]$$
Here \( k \) represents a specific component cost (e.g., site evaluation) and \( A_{i,j} \) is the estimated storage capacity at the grid cell location \( i,j \) (for more details, see Appendix Section B2).

The total site costs (in eq. [22]) are then:

\[
C_{i,j}^{\text{site}} = \sum_{k=1}^{7} C_{i,j}^{k}
\]  

[23]

The dollar costs are adjusted to a 2007 USD basis, for which the PPI for oil and gas is similar to the preliminary PPI in 2010 (Bureau of Labor Statistics (BLS) 2010).

While this new version of our cost module now allows for a more comprehensive estimation of storage costs, we recognize that though regulations for sequestration have been developed in the United States (Environmental Protection Agency (EPA) 2010), site configuration, monitoring, and long-term liability practices for CO\(_2\) storage have not yet been established (Sally M. Benson et al. 2002; Hepple & S. M. Benson 2005), and that therefore many of the expenses compiled by the EPA are tentative. Furthermore, a number of these expenses will depend on how the site is evaluated, developed and monitored. As a base case, we assume there is one initial seismic survey to characterize each storage site (i.e. raster cell) and two follow-up monitoring surveys, and that the site is crossed by a relatively high 10 km of distribution pipelines, in addition to other minor monitoring infrastructure expenses (see Appendix Section B3 for more details as well as for a sensitivity analysis for these assumptions).

### 3.3. Results

The capacity and cost estimates produced by our model for the rasterized regions in the 15 deep-saline sandstone aquifers are shown in Figure 8. As can be seen, some of
these regions extend over most of the aquifer and likely reflect its storage potential, while other rasterized regions depict only a fraction of the aquifer and may not be representative of it. Regardless, all of the rasterized regions clarify several important aspects regarding storage capacity/cost, at least within these aquifers.

The first is that not all areas within the aquifers are suitable for storing CO₂ in a supercritical state. The grey portions of the rasterized regions are locations where pressures and/or temperatures within the aquifers do not appear to be sufficient to keep the CO₂ supercritical. Generally this occurs where the aquifer is too shallow.

Secondly, locations within the rasterized regions that can support supercritical CO₂ storage (colored regions, Fig. 8) have estimated capacities and costs that are not constant. This holds not only from one aquifer to the next, but also within aquifers. For example, storage capacity throughout much of the rasterized region in the Frio aquifer (#7, Fig. 8A) is high, approaching or exceeding 8Mt CO₂ per grid cell. For the Oriskany aquifer (#13, Fig. 8A), however, the storage capacity per grid cell is not only an order of magnitude less, but also much more variable, with estimates ranging between ~100kt-1Mt CO₂ per grid cell.

A third point is that the variability in storage capacity and cost is not well represented by simple averages. Some aquifers like the Frio and Mt. Simon are dominated by high capacities and low costs, while others exhibit a much more complex mix of capacities and costs, such as in the Lyons, Oriskany, and St. Peter aquifers (#5, #10 and #13, Fig. 8A, respectively). This is even clearer in Figure 9, which shows frequency plots of the estimated storage capacities and costs for the aquifers. These plots are non-Gaussian and many are skewed toward a higher frequency of either lower capacity or lower cost sites with long tails that extend out one or more orders of magnitude.
magnitude. There is a considerable discrepancy between these plots and the average estimated storage capacity and cost for the rasterized regions in the aquifers (see key in Fig. 9). The average estimated storage capacity within all the rasters is a relatively high \(~500,000\text{ tonnes/km}^2\) (median 133,000 tonnes/km²) while the average estimated cost is an extremely high $106/\text{tonne}$ (median $15.50/\text{tonne}$). This is the result of the long tails on the frequency plots (Fig. 9) biasing the averages upwards and giving the impression that the aquifers have much higher capacities and costs than are evident in the frequency plots, a point we return to later.

Figure 9: Distribution of Quantity and Cost in Analyzed Areas. A PMF of quantity (A) and cost (B) cells shows highly skewed distributions for all basins. The figures in the legend show the average, minimum, and maximum values for each formation; the Glen Canyon and Pottsville formations had no storage available in the analyzed area, so they are not included. The Repetto formation had too few cost cells to be adequately represented by the bins in this PMF, but has a similar distribution of cost and quantity cells.

Finally, the distributions of estimated capacity and cost in Figure 8 show a general correspondence with one another. Where the storage estimates are high, such as in the Frio and Mt. Simon rasterized regions, estimated costs tend to be low. And where
the storage estimates are on the lower end, such as in rasterized regions within the
Oriskany, Lyons and Fox Hills/Lower Hell Creek (#4, Fig. 8) formations, estimated costs
tend to be high.

This inverse relationship, however, is not as strong as it might appear from
Figure 8. Figure 10 is a scatter plot of storage capacity vs. cost for every grid cell in
Figure 8 where CO$_2$ could be stored in supercritical form (i.e., all the colored cells). The
plot shows a clear but very broad trend of lower estimated storage costs for grid cells
with higher estimated storage capacity. Note that the plot axes are in log scale, so even
though there is a trend, the capacity-cost relationship is still highly variable and appears
to be heteroskedastic. For example, at grid cells where storage would approach
$1000/\text{tonne}$, capacity estimates span $<10^4$ - $>10^6$ t/km$^2$, while lower costs require cells
that could store at least $10^5$ t/km$^2$. The plot indicates that high storage capacity per unit
area is a necessary but not sufficient condition for low cost.

This considerable variability is because estimated cost depends on more than just
storage volume. As equations [19] and [20] indicate, other key geologic variables
affecting cost are the permeability and depth of the aquifer. Nonetheless, storage
volume, and specifically sediment thickness at a site appears to be the most important
influence on cost. A linear regression of log-transformed capacity on log-transformed
injection layer thickness yields a relationship with an $R^2$ of 0.98 ($R^2 = 0.71-0.99$ for
individual formations), while a linear regression of log-transformed cost on log-
transformed injection layer thickness yields a relationship with an $R^2$ of 0.62 (from $R^2 =
0.11-0.99$ for individual formations). This leads us to conclude that layer thickness is a
reasonably good site-screening criterion because of the intrinsic link between thickness,
high capacity, and low cost.
Figure 10: A log-log plot of cost vs. quantity shows an inverse power law relationship, with considerable variation to the right of the trend line. The distribution exhibits heteroskedasticity but the variance and skew are both high for all values of the variables. Note that high capacity appears to be a necessary but not sufficient condition for very low costs. Only 1 in ten data points (~50,000 total) are plotted.

This link also has an important impact on the marginal abatement cost curves we construct from these estimates. Four MACCs are shown in Figure 11: one for the rasterized region in the Mt. Simon aquifer (#12, Fig. 8A), another for the region in the Frio aquifer, an aggregate MACC for the remaining basins, and an aggregate MACC for all of the rasterized regions in Figure 8. Each of these MACCs is in fact depicted as a band of possible estimated capacity-cost curves. This is due to the uncertainty over the distribution of sandy layers within the aquifers. As noted previously, we address this uncertainty by representing the sandy layers as a single unit with a thickness equal to
the net sand thickness of the reservoir based on the BEG data. The lower and upper bounds to the MACCs (i.e. the left and ride sides of the bands) are determined by solving for storage capacity and cost when this unit is placed at the bottom and then top of the aquifer, respectively. As the Mt. Simon formation is essentially all sandstone, there is no difference between the two and it is plotted as a line. The difference for the Frio and the total aggregate, however, is considerable.

All four MACCs reflect the non-normal distribution of storage capacities and costs within the rasterized regions. In fact, the MACCs reveal that the bulk of available storage capacity is relatively inexpensive (see Fig 11). For our base-case scenario, the minimum cost for storage is \(~$0.50/t \text{CO}_2\); 190 out of a total of 302 Gt of storage potential are available for less than $1/t, with nearly 260 Gt at or below $3/t and almost 275 Gt at or below $5/t. Note that all of these costs are considerably lower than the simple average estimated cost of storage mentioned previously, which is \(>$100/\text{tonne,}\) and even far below the median, which is $15.50/\text{tonne}.

In fact given the shape of the MACCs, a much more meaningful expression of the average is the cumulative mean cost of storage as a function of cumulative capacity \(x\) (i.e. the horizontal axis of Fig. 11)

\[
\int_{0}^{x} MACC(x) \, dx \\
\int_{0}^{x} MACC(x) \, dx \\
\int_{0}^{x} MACC(x) \, dx \\
\int_{0}^{x} MACC(x) \, dx
\]

This function for the aggregate MACC, which represents the average cost of storage at all the sites (i.e. cells) that sum up to a given cumulative capacity, is also plotted in Figure 11. The function shows that 260 Gt or 87% of the storage analyzed could potentially be utilized for an mean cumulative cost of \(<$1/t \text{CO}_2\), and that all of the storage could be utilized for a mean cumulative cost of \(<$5/t \text{CO}_2\) (Fig 11).
Figure 11: The curves show the marginal cost of storage within a range bounded by concentrations of sand at the top and bottom of formations for the Mt. Simon (red; top and bottom are the same), the Frio (green), the remaining formations (orange) and all 15 analyzed formations (blue). The average cost of abatement for all basins for a layer at the top of a formation (corresponding to the upper bound of the blue region) is also shown. Cost is on a 2007 USD basis and is truncated at $100 per tonne.

The two largest contributors to the aggregate MACC are the Frio and Mt. Simon aquifers. The Frio represents 62% of all the storage evaluated, while the Mt. Simon constitutes another 21%. This is in part because a number of the other aquifers are underrepresented by the regions we were able to rasterize, including the Glen Canyon, Morrison, and Cape Fear (#2, #3 and #15, Fig. 8A). However, the Frio and Mt. Simon
aquifers also overshadow the other aquifers because they have considerable storage capacity at relatively low cost that is far in excess of their surface area. The Frio, for example, makes up only 14% of all the rasterized areas analyzed, while Mt. Simon makes up only 5% of the area analyzed, and would dominate the aggregate MACC if the Frio were removed.

Given that they constitute some 83% of the aggregate MACC, it follows that the Frio and the Mt. Simon aquifers have distributions in which the vast majority of the estimated storage capacity is available at a relatively low estimated cost. In the case of the Frio aquifer, up to 184 Gt of CO₂ storage (or 61% of the storage analyzed) has an estimated cost of <$1, while in the Mt Simon aquifer, up to 33 Gt of CO₂ storage (11% of the storage analyzed) is estimated to be available for <$2/tonne. What is significant, however, is that the MACCs for many of the other individual rasters share this same type of distribution (Fig. 9), indicating that while absolute costs may vary between the aquifers, relative costs within the aquifers are similarly distributed, with most available storage clustering near the low end for cost.

This common shape to the MACCs holds even when variables in our model that affect the absolute values of our capacity and cost estimates are changed. Among the least constrained of these variables is the capacity factor. Research by van der Meer et al (Bert van der Meer & Egberts 2008; Lubertus van der Meer & van Wees 2006), Birkholzer and et al (Birkholzer & Q. Zhou 2009; Birkholzer et al. 2009) and Nicot (2008), indicates that the effective capacity factor is reduced if the pressure within the reservoir needs to be managed as it fills with CO₂. While our injection module includes pressure constraints, our capacity module does not, so our model may be overestimating storage capacity and in turn underestimating storage costs. We evaluated what impact this
might have on the MACCs by reducing the capacity factor eight fold to 0.5% and then repeating our analysis. In the resulting aggregate MACC, storage costs roughly doubled but the shape of the supply curve remained the same.

We also explored to what degree the shape of our MACC is influenced by the various cost components for the storage site, such as site evaluation and monitoring. Figure 12 presents the cost distributions for each of these components as estimated from all grid cells in the rasterized regions where supercritical storage of CO₂ would be viable. The distributions are displayed as a box and whisker plot. In this type of plot, the interquartile range is shown within the boxed region (the 25th to 75th percentile) with a line for the median, and the whiskers are plotted at 1.5 times this interquartile range beyond the boxes. Outliers are plotted outside the whiskers. In the case of the rasterized regions, all outliers are above the high cost whiskers and are so numerous that the dots form lines (Fig. 12). This is a direct reflection of the long tails to the total cost distributions shown Figure 9.

There is considerable variation in the contributions of the different cost components to the total cost, but the estimates summarized in the whisker plot indicate that the injection wells are the most significant cost component in our analysis. For example, the ratio of the median injection cost to the median total cost is 2:3. The next two important costs are for site characterization and monitoring; the ratios of these to the median total cost are 1:10 and 1:6, respectively, with the three remaining cost components constituting just 1:12 of the median total cost. Note that in our model, injection well costs (i.e., \( C_{i,j}^{\text{drill}} \) and \( C_{i,j}^{\text{inj}} \) in eq. [21]), which dominate the total estimated cost for storage, are a function of site geology. Site geology is also the fundamental control on the shape of our MACC. Thus we conclude that varying the component costs...
will affect the absolute estimates for storage costs produced by our model, but not significantly alter the distribution of costs represented in our MACC.

Figure 12: Distribution of Cost Components. A box-and-whisker plot of the total distribution of costs and the distribution of cost components by category (labeled on the x-axis, with “base model” referring to the costs in Eccles et al (2009) for comparison and the remaining categories drawn from the EPA cost assessment) shows the variation in costs of all valid cells with storage potential (roughly 500,000) over several orders of magnitude. The red lines above the whiskers are outliers, which are numerous enough to be unable to distinguish them individually.

3.4. Discussion

Our storage-based MACCs of select regions within a number of deep-saline sandstone aquifers reveal that, at least in the regions we have analyzed, areas with high estimated storage capacity also tend to have low estimated storage cost. This connection
persists even when variables that have a strong influence on the cost estimates produced by our model are changed substantially.

Two other factors could affect the shape of our MACCs, one of which is the accuracy of our model in predicting storage capacity and injection rates. This accuracy is discussed at length in Eccles et al. (2009) where among other things we find that our predictions of injection rates for geologic conditions approximating those at current CO₂ storage demonstration projects (i.e. Sleipner West, Frio, Nagaoka) fall within the injection rate limits reported at these projects. We also discuss, as we do in this paper, how our capacity module is similar to that developed by others. This module is also similar to that used in NATCARB for estimating the storage capacity of the same deep-saline sandstone reservoirs analyzed here. A direct comparison of the estimates is not appropriate given differences between the studies in the spatial extent to which the aquifers were evaluated. But our storage estimates for these reservoirs are in line with those reported by NATCARB (see Table 2), which likewise shows vast storage potential in the Mt Simon and along the Texas Gulf Coast, similar to other studies (Department of Energy (DOE) 2010; Stefan Bachu 2003). These similarities plus the favorable comparison of our injection rate estimates with data from demonstration projects suggests the shape of the MACCs in Figure 11 is not the result of potential problems with our model.
Table 2: Comparison of Capacity estimates with NATCARB

<table>
<thead>
<tr>
<th>Map Index</th>
<th>Formation</th>
<th>Storage (Billion Metric Tons)</th>
<th>Notes</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Total Estimate</td>
<td>NATCARB low</td>
</tr>
<tr>
<td>1</td>
<td>Repetto</td>
<td>0.16</td>
<td>1</td>
</tr>
<tr>
<td>2</td>
<td>Glen Canyon</td>
<td>0</td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>Morrison</td>
<td>0.73</td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>Fox Hills</td>
<td>5.7</td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>Lyons</td>
<td>5.5</td>
<td></td>
</tr>
<tr>
<td>6</td>
<td>Granite Wash</td>
<td>9.4</td>
<td></td>
</tr>
<tr>
<td>7</td>
<td>Frio</td>
<td>187</td>
<td>17</td>
</tr>
<tr>
<td>8</td>
<td>Woodbine</td>
<td>10.8</td>
<td>5</td>
</tr>
<tr>
<td>9</td>
<td>Paluxy</td>
<td>1.7</td>
<td>5</td>
</tr>
<tr>
<td>10</td>
<td>St Peter</td>
<td>7.9</td>
<td>0.6</td>
</tr>
<tr>
<td>11</td>
<td>Pottsville</td>
<td>0</td>
<td>1.1</td>
</tr>
<tr>
<td>12</td>
<td>Mt Simon</td>
<td>64</td>
<td>17</td>
</tr>
<tr>
<td>13</td>
<td>Oriskany</td>
<td>4.4</td>
<td>0.7</td>
</tr>
<tr>
<td>14</td>
<td>Cape Fear</td>
<td>1.2</td>
<td>12.6</td>
</tr>
<tr>
<td>15</td>
<td>Potomac</td>
<td>3.8</td>
<td>2</td>
</tr>
<tr>
<td>16</td>
<td>Tuscaloosa</td>
<td>5</td>
<td></td>
</tr>
</tbody>
</table>

Another factor that could affect the shape of the MACCs is the inclusion of additional aquifer areas and even other aquifers in our analysis. For example, the BEG dataset underrepresents the Mt. Simon formation, which could rival the Frio in storage potential (Barnes et al. 2009). And because our current model is for sandstone aquifers,
we do not even address the storage potential of deep-saline carbonate aquifers, which calculations by the BEG (2000) and NATCARB (Department of Energy (DOE) 2010) suggest could have storage capacities approaching those of the Mt. Simon and Frio aquifers.

Inclusion of more aquifer regions would raise the absolute storage capacity in our MACC, but it is not clear to us that additional data on these or other aquifers would also significantly alter the shape of the MACC. We find no significant correlation between the considerable variation in density of the BEG data and our estimates of storage capacity and cost. This suggests to us that while increased data density is likely to refine our capacity estimates for the aquifers, it will not necessarily change the weighting of the MACC toward high-capacity/low cost storage. Furthermore, inclusion of more low-capacity/high-cost regions in our analysis (those represented by the right, upward rising side of the MACC) is not likely to add enough storage capacity to diminish the extent of high-capacity/low-cost regions already included in the MACC (i.e. shift the curve left). And the inclusion of more high-capacity/low-cost regions (the flat, left side of the MACC) will simply enhance the current shape of the MACC by increasing the cumulative capacity of low-cost storage areas (i.e. shift the curve right).

An underlying cause for the shape of the MACC appears to be that cost and capacity are inversely related through the net sand thickness of the reservoir. Thick reservoirs have high bulk volume and can physically store the most CO₂, so they will make up the majority of storage in a sink-based MACC. Thick reservoirs will also be relatively low cost because the major cost components depend on injection rate (\(Q_{\text{mass}}\) through \(Q_{\text{site}}\) and \(n\) in eq. [22]), which increases with net sand thickness, and they depend on the area over which the plume of injected CO₂ will spread away from the injection
well \((A_{ij} \text{ in eq. [23]})\), which decreases with net sand thickness. It is certainly possible that some reservoir regions may be low-cost because of high permeability. However, unless these regions are also thick, their bulk volume will be low and their affect on the MACC will not be significant. For the same reasons, high cost, low capacity regions will also not have a significant affect on the MACC. Consequently, we believe that this connection between relatively high-capacity and low-cost storage is likely to be one of our most robust results, a promising conclusion for proponents of CCS if correct.

As stated previously, however, CCS will only see widespread deployment if it is cost effective, and probably the most tentative estimates produced by our model are those relating to costs. Our estimates are almost certainly not an upper bound on storage costs. As previously stated, site configuration, monitoring, and long-term liability practices have not yet been established (Sally M. Benson et al. 2002; Hepple & S. M. Benson 2005), and we do not include other potentially significant expenses such as compensating property owners (Gresham et al. 2010). Nonetheless, our assumptions and modeling yield average storage costs that are very close to those arrived at by Middleton and Bielicki (2009) using a similar injection model for a fixed set of geological properties, and our ranges for storage costs evaluating a wider set of properties are similar to those of Wildenborg et al (2004). In fact, we are able to find previous cost estimates for CO\(_2\) storage that range over much of our MACC (Bock 2002; Hendriks et al. 2004; W. G. Allinson et al. 2003; BCG 2008; McKinsey Climate Change Initiative 2008; Al-Juaied & Whitmore 2009). This is because nearly all of the costs reported, from the <$1 tonne/y in Bock (Bock 2002) to the >$10 tonne/y in Al-Juaied and Whitmore (Al-Juaied & Whitmore 2009), are reasonable given some geological parameters. Therefore, the problem lies not necessarily with the methodology for calculating these costs but rather
the manner in which they are reported, which to date has been in terms of simple mean costs or even costs derived from reservoir properties at a single wellsite. For example, in our previous paper (Eccles et al., 2009), we did not account for the spatial distribution of the aquifer properties we analyzed and arrived at an “average” storage cost of ~$3/tonne, a figure that was in line with others’ estimates. Here we do account for the spatial distribution of the reservoir properties and when we calculate a simple average cost as before, we arrive at >$100/tonne. Only when the capacities and costs are considered together in a spatial framework does it become clear that low cost regions are also high capacity regions, meaning that much of the storage capacity of the aquifers we evaluated is estimated to be low cost. And because the capacity and cost distributions are not uniform, simple averages are not only inaccurate, they can lead to an overestimate in the cost of storage in aquifers with considerable geologic heterogeneity.

Simple averages or single estimates of storage capacity and cost are also misleading in terms of where to sequester CO$_2$ in aquifers. Many of the rasterized regions in Figure 8 have sub-regions of high-capacity/low-cost storage that occur in different parts of an aquifer. Linking these higher quality storage sites to CO$_2$ point sources via pipelines could require different transport routes and thus transport distances to the aquifers. To date, studies using transport modeling have done the best job integrating the cost of transportation and storage. Middleton and Bielicki (2009), McCoy and Rubin (2008a), and Wildenborg et al (2004) among others have developed transport optimization algorithms that can take into account geologic and economic differences between storage sites. The disclosure of costs in these studies, however, is generally in the form of summary statistics (e.g. mean and standard deviation (Middleton & Bielicki 2009)), which as we have discussed can under-represent the true
variation in storage costs, and assumes them to be normally distributed, which is probably incorrect. Other studies give no hint that spatial or geological variability is even considered. Supply curves (representing integrated costs of storage and transport, compiled by a different method than ours) for North America and China by Dooley et al (2004) and Dahowski et al (2009), respectively, rely on a method for characterizing cost in all saline aquifers based on a single value for injection rate (computing injection cost only) and never disentangle the cost of storage in saline aquifers from transport except for two examples (with the same cost of storage) shown graphically in a subsequent report (Dooley et al. 2008).

If the cost of storage varies on the same scale as the cost of transport, which our analysis supports, the optimal transport configuration must take into account variations in storage capacity (McCoy & Rubin 2008a; Middleton & Bielicki 2009; Gresham et al. 2010). Without differentiating the cost at the end of the transport stage, the transport optimization algorithm will not map cost-efficient or possibly even practical routes for transporting CO₂ from sources to sinks. The algorithm will also not calculate the integrated cost of transport and storage correctly. Variability in storage costs is therefore important in determining both the overall viability of the integrated CCS system as well as the ultimate configuration of the transport-storage components of the system. A few regions with relatively high-capacity, low-cost storage potential dominate the bulk of the MACC in our analysis. These regions constitute some 83% of the storage potential, but only 19% of the total surface area of the aquifer regions we analyzed. The remainder tends to have lower storage capacity at higher estimated cost. Our analysis is limited, however, and should not be used to exclude regions of the country as not having good storage potential. There are undoubtedly sites within many of these lower quality
aquifers that when transportation expenses are included could still prove to be cost-effective storage sites for certain CO$_2$ point sources. However our analysis does suggest that not all CO$_2$ sources will have cheap transport access to high-quality storage sites. If this is the case, the configuration of the national transport and storage system might look quite different than a set of shortest pathways from CO$_2$ sources to a relatively homogenous group of saline aquifer storage options such as that depicted by Dooley et al (Dooley et al. 2004).

In fact with the incorporation of more and possibly better data, our storage-based maps and MACCs would have greater value as a component of the type of comprehensive transport modeling conducted by Dooley et al (2004). Integrated assessments of the entire CCS system will be more accurate when they take into account the vast heterogeneity in geosequestration potential in saline aquifers and will better inform policymakers and industry on the true potential, costs and configuration of CCS as an emissions abatement option.
4. Impact of Geological Variability on Geosequestration Site Footprint

4.1. Introduction

In the next century, the impact of anthropogenic greenhouse gas (GHG) emissions on Earth’s climate could end up harming ecosystems, and altering human civilization (Bernstein et al. 2007). Carbon capture and storage (CCS) is one technological approach that can help curtail the release of these emissions to the atmosphere (IPCC 2005). The storage component of CCS, or geosequestration involves the injection of CO$_2$ kilometers below the Earth’s surface into rocks such as sandstones that are capable of serving as geologic reservoirs for the gas. Such rocks are abundant and their estimated storage capacity is large (John Bradshaw et al. 2007), but due to geological heterogeneity, the cost for this form of storage remains uncertain and a focus of considerable research (Dooley et al. 2004; Eccles et al. 2009). For example, deep saline aquifers are estimated to have the largest storage potential of possible geologic reservoirs for CO$_2$. The basis for storage cost estimates in these reservoirs ranges from simple averages that are generalized to all such aquifers (Dooley et al. 2004; Dahowski et al. 2009) to highly detailed techno-economic modeling of individual reservoirs (Rubin 2008; Middleton & Bielicki 2009; Gresham et al. 2010). Neither approach, however, includes the cost of getting the CO$_2$ from a central receiving point at a storage site to multiple injection wells in the event the stream of incoming CO$_2$ is too large to be handled by one well. In fact, multiple wells are likely to be needed to sequester the CO$_2$ emissions coming from large point sources, such as coal-fired power plants (McCoy & Rubin 2008b; Middleton & Bielicki 2009; Eccles et al. 2009; Gresham et al. 2010).
We develop two end-member models for calculating the minimum cost of developing a system for distributing CO\textsubscript{2} about a sequestration site. We define this system as the network of pipelines connecting a central receiving point for CO\textsubscript{2} at a storage site to one or more injection wells. The cost for this system depends upon the mass of CO\textsubscript{2} to be stored, the injection rate at the wells, and their spacing. The results from our model suggest that the distribution system has the potential to be a significant component of the total cost of CCS. Furthermore, limits on the spacing of the injection wells could significantly increase the total footprint of the system. This in turn could end up leading to a downward revision of storage capacity estimates for candidate reservoirs while also making it more difficult to acquire rights to the total acreage needed for storage.

4.2. Models

4.2.1 Well Spacing

There are at least two ways injection wells might be optimally spaced about a storage site based on the geologic properties of the underlying reservoir. The first is to rely on bulk volume calculations and what is usually called a capacity factor or sweep efficiency in combination with an injection rate. We refer to this as the \textit{capacity} model, since it essentially determines how much space each well would need to fully sequester CO\textsubscript{2} over a project lifetime (illustrated in Figure 13). The second is to space wells based on pressure interference. This approach, which we call the \textit{interference} model, relies on determining the degree to which injection wells might interfere with each other and increase the pressure in the reservoir reducing the rate at which CO\textsubscript{2} can be safely injected (also illustrated in Figure 13). Both models are formulated as follows.
The methods for evaluating the correct well spacing using different premises are shown in the figure. The failure mode in each method (i.e. the result of incorrect well spacing) is shown schematically. In the capacity method, wells that are too close together will not have enough physical bulk volume to inject the required CO2. In the interference method, wells that are spaced too closely will experience the increase in background pressure caused by nearby wells, reducing injection rate. The injection environment displayed is highly simplified; note that (for example) Well 2 would impact Well 1 symmetrically, which is not shown.
4.2.1.1 Capacity Model

This model calculates well spacing by first evaluating the mass-per-unit-volume capacity of the reservoir to store CO$_2$, $C_{unit}$. Following along the lines established by others (John Bradshaw et al. 2007; Stefan Bachu et al. 2007; Department of Energy (DOE) 2010; R Burruss et al. 2009) this is given by

$$C_{unit} = \rho_{CO_2}(T, P) \phi \epsilon$$  \[24\]

where $\rho$ is the density of CO$_2$ as a function of temperature ($T$) and pressure ($P$), $\phi$ is the porosity of the reservoir, and $\epsilon$ is the capacity factor or sweep efficiency. For this analysis, we use values for $\rho$, $\phi$, $T$, $P$ and that are drawn from the study by Eccles et al (Eccles et al. 2009) of deep sandstone saline aquifers in the United States. However, $\epsilon$ requires additional numerical modeling to determine; we evaluate our model with 4% reported by Doughty et al for injection into sandstone aquifers (Doughty et al. 2001).

Next we determine the surface footprint associated with $C_{unit}$, which is the minimum area under which CO$_2$ from one injection well could theoretically be stored

$$A_{well} = \frac{Q_{mass} \cdot l}{C_{unit} \cdot b}$$  \[25\]

In this equation, $Q_{mass}$ is the annual injection rate of the well, $l$ is the project lifetime, and $b$ is the injection layer thickness.

$A_{well}$ can have an irregular shape due to reservoir properties and geometry, however for simplicity we approximate it as being square and calculate the average well spacing ($W_{cap}$) as

$$W_{cap} = \sqrt{A_{well}}$$  \[26\]
4.2.1.2 Interference Model

Note that in the capacity model, the injection rate is assumed to be constant and unaffected by the injection of CO$_2$ at adjacent wells (Eq. [25]). We develop a different approach, the interference model, to calculating the average well spacing (in this model, $W_{int}$) considering the pressure interference from adjacent wells. Minimizing pressure interactions between injection wells can be addressed using the Theis solution, an application of radial integration of Darcy’s law (Freeze & Cherry 1979). By simplifying the Theis solution, we arrive at a general model describing the pressure interference experienced by any given well in a multiwell system.

Unlike the equations in the capacity model, this analysis does not yield a simple equation that relates the average well spacing to a function of other parameters (like Eq. 3). For this reason, we develop a regression using the variables in the simplified pressure interference model to relate $W_{int}$ to a function of other parameters. We generate data for this regression with systematic variation of the parameters in the simplified well function model, allowing us to produce an equation of the necessary form (i.e. $W_{int} = f(x)$).

The Theis solution describes the change in reservoir pressure, $\Delta P$, in terms of hydraulic head, $h$, which are caused by flow through the porous media around a well. The solution at an arbitrary distance from the well is time dependent, i.e.

$$h_0 - h(t) = \frac{Q}{4\pi X} ei(u)$$  \hspace{1cm} [27]

The dummy function, $ei(u)$ is the exponential integral of

$$u = \frac{r^2 S}{4 Xt}$$  \hspace{1cm} [28]
\( h_0 \) is the hydraulic head at time zero, \( t \) is time, \( r \) is the distance from the well, \( Q \) is the injection rate at the well, and \( X \) and \( S \) are, respectively, the transmissivity and storativity of the reservoir (Freeze & Cherry 1979).

Of concern here is the change in pressure, \( \Delta P \), relatively close to an injection well, which can be represented as

\[
\Delta P \propto ei(u)
\]

[29]

Note that the absolute relationship between \( P \) and \( ei(u) \) is unimportant, as we are interested only in the increase or decrease in *relative* pressure or pressure “interference” between wells in a distribution system. Assuming that the wells have similar injection rates, this can be expressed as the following linear superposition of terms from the Theis well solution (Freeze & Cherry 1979) for wells 1 to \( n \)

\[
\Delta P \propto ei(u_1) + ei(u_2) + \ldots + ei(u_n)
\]

[30]

The *influence* \( I \) of multiple wells on a single well within the distribution system we define as the change in pressure measured at \( r_i \) for a given well (well 1) in a multiwell system (i.e. a system having many wells spaced at \( r_2 \ldots r_n \) from the first well) compared to the pressure for that well 1 if the wells spaced at \( r_2 \ldots r_n \) were not there at any time \( t \):

\[
I = \frac{\Delta P_{1\ldots n}}{\Delta P_1} = \frac{\sum_{i=1}^{n} ei(u_i)}{ei(u_1)}
\]

[31]

\( I \) is the ratio of the multiwell pressure system to the pressure that would exist from a single well by itself, i.e. the degree to which other wells around the first well are making it more difficult to inject CO\(_2\). Note that \( I \) is dimensionless.
Equations [28] and thus [31] require the storativity and transmissivity of the reservoir. The transmissivity is given by

\[ X = Kb \]  

[32]

where \( K \), the hydraulic conductivity of the reservoir, is related to reservoir permeability, \( k \), via

\[ k = K \frac{\mu}{\rho_f g} \]  

[33]

In this equation, \( \mu \) is the dynamic viscosity of the pore fluid, \( \rho_f \) is the pore fluid density, and \( g \) is the gravitational constant.

The storativity of the reservoir is given by

\[ S = S_s b \]  

[34]

in which \( S_s \) is the specific storativity given by

\[ S_s = \rho_f g (\alpha + \phi \beta) \]  

[35]

Here \( \alpha \) is the compressibility of the rock matrix and \( \beta \) is the compressibility of the pore fluid.

Substituting equations [32-34] into [28] and canceling like terms yields the following revised expression for \( u \) at each well \( i \)

\[ u_i = \frac{r_i^2 S_s}{4Kt} \]  

[38]

In our analysis, we had to select the number of wells to consider for \( n \) in [31]; we assumed a 25-well square grid (24 wells surrounding well 1), which allows us to reduce \( r_i \) in (13) for \( i=2...n \) to several functions of a single value, \( W_{inj} \), the well spacing between two wells, through simple geometric relationships for right triangles and allowing \( u_i \) to cancel, since it appears in both the numerator and denominator of [31]. We explored
alternative options including both more wells and fewer; the results do not change significantly beyond a 5-well system (with 4 wells equidistant from the well 1), which is likely to be close to the minimum number of wells required for a site handling one or more power plants’ emissions under ideal injection conditions such as those found in the Utsira Sand for the Sleipner West injection project (Eccles et al. 2009). If injection rates such as those determined in Eccles et al both at injection pilot projects and for average reservoir properties are typical of real-world injection scenarios, using \( n = 25 \) (meant to approximate \( n \geq 25 \)) is likely to be representative for the majority of injection projects.

This leads us to a final relationship between influence \( (I) \) and other variables:

\[
I = \sum_{i=2}^{25} e^i \left( \frac{f_i(W_{int})S_s}{4kt} \right) \tag{39}
\]

where \( f_i \) is the function relating the well grid distances to the spacing between two wells \( W_{int} \) (see Fig 14). Of the reservoir properties encompassed in [39] and by extension [33] and [35], only permeability varies substantially enough (i.e. over several orders of magnitude) to affect the value of \( I \) in [31]. As noted earlier, [39] is not in a form that is particularly valuable for site planning, which is to say that it is difficult to solve [39] for \( W_{int} \). Thus we go a step further and develop a simpler, empirical version of the equation in which we calculate \( W_{int} \) as a function of permeability and influence.
Figure 14: Illustration of Well Grid Distances. A quadrant of a 25-well grid is shown, with the distances as a function \((f_i(W) \text{ in (14)})\) of the space between two wells \((W)\) shown. Wells \(i=2\ldots7\) are displayed; Wells \(i=8\ldots13\) will be the same, and so on.

We do this by using \([39]\) to calculate multiple values for \(l\) based on arbitrary well spacings and a range of permeabilities taken from sedimentary formations described in Eccles et al(2009) (See Fig 15). Given the functional form of the Theis curve, it was likely that the results would involve a power law function of \(k\), which exploratory data analysis showed to be the case, leaving us with a regression on our numerical simulation results of the form

\[
W_{ij} = \beta_0 + \beta_1 \sqrt{k}.
\]
Figure 15: Well Spacing Model Regression. Eqn 14, the model relating Interference, Permeability, and Well spacing is used to generate a systematic evaluation of many possible combinations of parameters (shown as black dots). Our regression on this data (Eqn 18) is shown as the colored surface.

This form ignores (or collapses into $\beta_m$) significant variation over time, as multiple wells will barely influence each other at all in the initial stages of injection and will asymptotically approach the new equilibrium pressure as $t$ goes to infinity. Since there is no way to avoid pressure interference over time, site planners or operators will instead have to pick the degree of influence they would tolerate after a given amount of time. We chose to fix $t$ in the numerical simulations of [39] for a regression to determine the values of the coefficients of [40] at a constant value of 20 years and allow $I$, now called $I_{20}$ to indicate it is fixed to a certain point in time, to vary such that operators could...
select the amount of influence they would be willing to tolerate 20 years after injection begins. This would be under the understanding that this influence would be less than the value selected in the first 20 years of the project and more if injection continues beyond 20 years.

Since the constant $\beta_0$ is orders of magnitude smaller than $W_{\text{inj}}$ in [40], we discard it and examine the value of $\beta_1$ as it is related to the degree of influence discussed above, $I_{20}$ which results in the exponential function

$$\beta_1 = -445.1 \ln(I_{20}) + 2656.5 \quad [41]$$

where $I_{20}$ is expressed as a percent representing the increase in background pressure in the wellbore the site operator is willing to tolerate after 20 years, collapsing $t$ and $I$ in [39] into a single term. The fit is optimized by adding an adjustment term for permeability, making the equation

$$\beta_1 = -445.1 \ln(I_{20} + 0.1888 \ln(k) - 14.221) + 2656.5) \quad [42]$$

In this form, the regression has an $R^2$ value of $>0.998$ and does not vary significantly with other factors in the determination of specific storativity and hydraulic conductivity (See Fig 15). Systematic variation (i.e. sampling from a uniform distribution) of pore fluid density and porosity over the full range of values found in aquifers can reduce this value to 0.885, but if these values are sampled from normal (or log normal) distributions, the $R^2$ values is 0.995. We conclude that the model has reasonable accuracy over nearly all reservoir conditions but near-perfect good accuracy for all permeabilities and ranges of pore fluid density from 1000-1150 kg/m$^3$ and porosities from 0.2 to 0.35 (roughly corresponding to depth ranges of 1000 to 2000 m).
Equation [42] then allows us to determine the closest well spacing \( W_{\text{inj}} \) (in meters) that minimizes interference between wells as a function of well influence \( I_{20} \) (percent) and permeability \( k \) (in millidarcies)

\[
W_{\text{inj}} = -445.1 \ln(I_{20} + 0.1888 \ln(k) - 14.221) + 2656.5 \times \sqrt{k}
\]  

[43]

We emphasize that although this equation can be used for convenient calculations of injection spacing, it is an approximation for the relationships found in [39] and aside from the functional relation to the Theis curve does not reflect the inherent physical properties of the injection system.

### 4.2.2 Distribution Pipeline Lengths and Cost

Once the well spacing has been determined, either by the capacity or interference model, the lengths and total cost of the distribution pipelines needed to connect the wells to the receiving point for \( \text{CO}_2 \) can be estimated. Given the mass of \( \text{CO}_2 \) mass to be sequestrated, \( Q_{\text{tot}} \) and the average rate at which it can be injected into an underground reservoir at a well site, \( Q_{\text{mass}} \) the number of wells, \( N_{\text{well}} \) required to handle \( Q_{\text{tot}} \) is

\[
N_{\text{well}} = \frac{Q_{\text{tot}}}{Q_{\text{well}}}
\]  

[44]

The configuration of these wells about a storage site will vary depending on cost as well as the shape and geologic heterogeneity of the reservoir. For simplicity, however, we assume that the wells are evenly spaced in a rectangular grid, so the number of rows of wells is

\[
N_{\text{well,}k} = \left\lfloor \sqrt{N_{\text{well}}} \right\rfloor
\]  

[45]
where [...] signifies the next nearest integer. Correspondingly, the number of wells in each row is

$$N_{\text{well},j} = \left\lfloor \frac{N_{\text{well},l}}{N_{\text{well},k}} \right\rfloor$$

[46]

$N_{\text{well},k}$ and $N_{\text{well},l}$ are then used to calculate the number and sizes of pipes needed to carry CO$_2$ to the injection wells. We subdivide these pipes into three distribution levels: primary, secondary and tertiary (Fig. 16). The length and mass flow of CO$_2$ through every pipe segment in each level is calculated using the equations listed in Table 3, with the pipes in tertiary section being increased by 10% to account for pipe bending, connections, etc. Finally, the lengths in the different levels are summed to arrive at the total length of pipe required per level (Table 3).

**Table 3: Calculation of pipe sizes for a CO$_2$ distribution network on a sequestration site (see Figure 16 for explanation of primary, secondary and tertiary pipes).**

<table>
<thead>
<tr>
<th>Pipes</th>
<th>Primary</th>
<th>Secondary</th>
<th>Tertiary</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of pipes</td>
<td>2</td>
<td>$N_{\text{well},l}/2$</td>
<td>$N_{\text{well},k}$</td>
</tr>
<tr>
<td>Length of each pipe</td>
<td>$(N_{\text{well},k} - 2)W/2$</td>
<td>$N_{\text{well},l}W$</td>
<td>$1.1W$</td>
</tr>
<tr>
<td>Mass flow in each pipe</td>
<td>$N_{\text{well}}\times Q_{\text{well}}/2$,</td>
<td>$2\times N_{\text{well},l} \times Q_{\text{well}}$,</td>
<td>$Q_{\text{well}}$,</td>
</tr>
<tr>
<td></td>
<td>if $N_{\text{well},l}/2 = \text{Even}$;</td>
<td>if $N_{\text{well},l}/2 = \text{Odd}$</td>
<td></td>
</tr>
<tr>
<td></td>
<td>$(N_{\text{well}}, N_{\text{well},l}) \times Q_{\text{well}}/2$,</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Next we calculate the diameters and costs of the total pipe lengths at each distribution level using the methods described in Chandel et al.(2010). The inner diameter (ID) of the pipe at a level is determined from the standard velocity-flow
equation for a fluid and assuming a design fluid velocity, $\bar{U}$, of 2.0 m/s (International Energy Agency Greenhouse Gas R&D Programme 2005).

$$ID = \sqrt{\frac{4Q_i}{\pi \rho \bar{U}}}$$  \[47\]

where, $Q_i$ is mass flow in each section of the network (in kg/s), and $\rho$ is the density of the fluid. For this, we assume that CO$_2$ is transported in a supercritical phase where $\rho$ = 846 kg/m$^3$ based on a constant temperature of 27°C and pressure of 13.0 MPa.

Figure 16: Schematic of a CO2 distribution pipe network at a sequestration site.

The thickness of a pipe at a level, $t$ (m), is then determined from the modified Barlow’s formula (McCoy & Rubin 2008a).

$$t = \frac{P_{\text{max}} ID}{2(S \cdot F \cdot E - P_{\text{max}})}$$  \[48\]
$P_{\text{max}}$ is the design pressure, which we set to 15 MPa; $S$ is the minimum yield strength of the pipe, which for existing North American CO$_2$ pipelines is 483 MPa (Mohitpour et al. 2003; McCoy & Rubin 2008a); $F$ is the design factor for safety, set to 0.72; and $E$ is the seam joint factor, which we set to 1.0, effectively assuming that the pipes are seamless (CFR 2010; McCoy & Rubin 2008a).

Pipes are sold according to their outer diameter, $OD$, determined via

$$OD = ID + 2t.$$ \[49\]

If the $OD$ is not a standard, commercially available size, then the $OD$ is set to next larger standard diameter. And if the $OD$ exceeds the largest available size, $OD_{\text{max}}$ (m), then the minimum number of pipes needed to transport the CO$_2$, $N_{\text{pipe}}$, is

$$N_{\text{pipe}} = \left\lfloor \frac{Q_i}{Q_{\text{max}}} \right\rfloor + 1$$ \[50\]

where $Q_{\text{max}}$ is the maximum mass flow in the largest diameter pipe and the brackets $\left\lfloor \right\rfloor$ represent the largest integer not greater than the enclosed ratio. In this latter case, $N_{\text{pipe}}$-1 pipes are of diameter $OD_{\text{max}}$ while the $N_{\text{pipe}}^{th}$ pipe carrying the remaining CO$_2$ is of inner diameter:

$$ID_{\text{pipe}}^{N_{\text{pipe}}^{th}} = \sqrt{\frac{4(Q_i - (N - 1)Q_{\text{max}})}{\pi \rho U}}.$$ \[51\]

Once the pipe diameters are determined, we estimate the costs for the length of pipe in each level of the distribution system and then aggregate these to arrive at the total cost for the entire distribution system. To calculate the cost of pipes, we assume that CO$_2$ pipelines cost the same as natural gas pipelines and use the price data published for the latter in Parker (2004). The per-kilometer cost of each pipe size is
determined by averaging the price data for each pipe size and discarding outliers (see Figure 17). The outliers are identified as the values that are above 1.5 times the interquartile range plus the third quartile or below the first quartile minus 1.5 times the interquartile range. These costs are updated for the year 2010 using the Global Steel Price Index for materials and the Chemical Engineering Plant Cost Index (PCI) for labor and miscellaneous costs (Chemical Engineering 2010). Note that, we do not include in the total right-of-way costs for building the pipelines as these are highly site specific and difficult to generalize. Instead we assume these costs are covered under the separate costs of securing the rights to store CO$_2$ at the site.

![Figure 17: Cost of pipeline. Capital cost ($/km) for different diameter pipes. The pipeline costs are estimated using data for existing natural gas pipelines published in 2004 (McCollum and Ogden, 2006).](image)

Finally, we annualize the total capital cost as
where $C_i$ is capital cost for the total length of pipe at each level $i$ in the distribution system, $n$ is operational lifetime of the pipes in years, and $j$ is a discount rate. We assume that the operational lifetime of the pipes is 25 y, and that the discount rate is 10%.

The annual operation and maintenance (O&M) costs for the pipes, $C_{O&M}$, are assumed to be 2% of total pipe cost after McCollum and Ogden (2006). Including these, the levelized cost of distribution system, $C_{levelized} ($/tonne), is

$$C_{levelized} = \frac{C_{annual} + C_{O&M}}{ton \ CO_2/y} \quad [53]$$

4.3. Results

The computed values for cost of distribution within a site, given a range of injection rates and well spacings (Figure 18), show that this component of CO$_2$ storage costs could range from negligible (<$0.10/tonne) to significant (>10/tonne). As Figure 18 shows, the costs for plausible injection rates (ranging from 0 to the maximum design injection rate at the Sleipner West project) and well spacings (ranging from the minimum to the maximum computed using both the capacity and well interference methods) vary over several orders of magnitude, meaning that the geological properties of reservoirs are critical in determining the total cost of geosequestration. Note that cost increases as nearly a linear function of well spacing, reflecting more or less directly...
proportional increases in the amount of distribution pipeline needed. For reservoirs with high injection rates, this constant increase in cost with well spacing is obviated by the fact that very few wells would be needed at a site that handles a fixed annual rate of CO₂ disposal. Distribution costs remain very low until well spacing approaches hundreds of kilometers. However, since there is an inverse relationship between total pipeline length and injection rate, there is a sharp nonlinear increase in the cost of distribution as injection rate decreases, shown in the figure along the y-axis. If well spacing is extremely low and injection rate is likewise poor, the cost of distribution is several dollars per tonne. As well spacing increases, the cost of distribution increases with it, leading to costs over $10 or even $100 per tonne.

Figure 18: Cost of Distribution Pipeline Network. The cost of distribution pipeline is shown as a function of well spacing (in meters) and injection rate (in tonnes per day). The surface illustrates the values calculated by the transport model.
and the mesh overlay represents a regression on those values (see text). Note that cost varies over several orders of magnitude; there are also discrete jumps in the transport model cost values as a result of discrete pipeline sizes available.

In the case of reservoirs with high injectivities of several thousand tonnes per day, such as Sleipner West (Eccles et al. 2009), the cost of distribution pipeline would likely be minimal (under $/1 tonne) unless the well spacing approaches a hundred kilometers or more. However, for other injection rates, such as the Frio pilot injection project (with injection rates in hundreds of tonnes per day (Eccles et al. 2009)), spacings of under 10 km could have distribution costs approaching $10 per tonne, rapidly rising to several times that with higher well spacing.

Pilot projects handle CO₂ volumes well under commercially viable scales such as the amount produced by one or more coal-fired power plants, which means they have not had the volume necessary to consider within-site distribution costs. Consequently, the scale of these costs has not been considered rigorously in literature. For example, Dooley et al in their cost curve analysis of CO₂ disposal in North America assume that all saline aquifers will have an injection rate of approximately 500 t/day, resulting in a combined transport and injection cost of roughly $5/tonne (Dooley et al. 2004), and later estimate it may approach $15/tonne (Dooley et al. 2008) (no explanation is given for the change in costs); if well spacing is greater that 15-25 km per well for these aquifers, the cost of distribution will be equal to or greater than the cost of transport and injection.

The surface in Figure 18 is an excellent candidate for a regression to simplify the calculation of the cost of distribution; the cost of distribution \( C_{\text{dist}} \) in USD/tonne is a function of well spacing \( W \) (in meters) and the per-well injection rate \( Q_{\text{mass}} \) (in tonnes per day):

\[
C_{\text{dist}} = 0.0096 \times W^{1.07} \times (Q_{\text{mass}})^{-0.72}
\]

[54]
In addition to considering the cost of these configurations, we considered the implications for the areal extent or footprint of a CO₂ disposal site. Since injection rates can be extremely low (such as the 48 tonnes/day at the Nagaoka pilot project in Japan (Eccles et al. 2009)), it is quite possible that dozens or even hundreds of injection wells would be needed to handle the thousands of tonnes per day a commercial site might be injecting. Additionally, we found that the range of plausible values for injection well spacing using either the capacity or the interference method was rarely below several kilometers (in the case of the capacity method) or tens of kilometers (in the case of the well interference method) and, as shown along the x-axis in Figure 18, could in some cases extend into hundreds of kilometers. While we believe sites would not be developed with such extreme requirements for well spacing, the footprint for geosequestration sites could be extremely large.

Figure 19 shows the relationship between number of wells (inversely proportionate to injection rate for a given site capacity), the well spacing, and the footprint of the site, expressed as contours ranging from a thousand square kilometers up to over 500,000 square kilometers. The relationship between the two is clear; if the number of wells is low and so is the spacing, the footprint is negligible. If either variable is marginal, however, the footprint can approach several tens of thousands of square kilometers. If both are variables are marginal, the site footprint will be over 100,000 square km. Again, if sites require too much space, it is unlikely that they would be developed, but even a relatively small site with 10 km between wells and 50 injection wells (for a single power plant, this would mean they would inject roughly 200 tonnes per day) would have a footprint larger than the state of Rhode Island.
Figure 19: Footprint of Sequestration Site. A contour map of storage site footprints shows that various combinations of number of wells and well spacing could lead to storage site footprints from well under 1000 square kilometers to several hundreds of thousands of square kilometers. Sites may have dozens or hundreds of wells because of either low injectivity per well or large site capacity. Sites may have very different well spacings ranging from under 10 km for a capacity model for calculating spacing or an average of 30 km for an interference model. Various state areas are plotted for comparison.

Based on these results, it is important to calculate the distribution of well spacing to evaluate the total cost of geosequestration including distribution pipelines. As indicated in the methods, we have two criteria on which to base well spacing calculations, the capacity model and the interference model. When used in the equations for the total length of pipe at each level in a distribution system (Table 3), the close well spacing produced by the capacity model yields a low cost estimate for a
distribution system, while the wider well spacing produced by the interference model leads to a higher cost estimate. These differences are illustrated with Monte Carlo simulation that draws realistic values for reservoir depth, temperature, pressure, layer thickness, porosity, permeability, and pore water density from uniform distributions that span the ranges for these properties in deep saline aquifers as summarized in Eccles et al. (Eccles et al. 2009). The simulation is used to produce comparative sets from the models well spacings and distribution system costs for an injection site sequestering 10 million tonnes of CO₂ per year over a period of 20 y. In the capacity model, we use a 4% capacity factor derived from modeling of sandstone aquifers (Doughty et al. 2001), within the range generally used for such bulk volume calculations (Stefan Bachu et al. 2007; Department of Energy (DOE) 2010; R Burruss et al. 2009; Birkholzer & Q. Zhou 2009). In the interference model, we make an assumption that the injection rate will have only declined 25% by the end of the project, which roughly corresponds to an average annual injection performance of 80-90% of the initial injection rate.

Using the capacity method, we find that well spacing is generally under ten kilometers for a uniform distribution of geological properties, yielding an average cost of approximately $1/tonne (see Figure 20), although it can range much higher than that. There is very low variance in this distribution, meaning that except for outlier regions, we could expect costs to be under $2/tonne. Similarly, Figure 19 shows that only very large sites with hundreds of wells would require footprints in the tens of thousands of square kilometers.

On the other hand, if we use a pressure interference criterion, costs are five times higher and have a much flatter distribution (see Figure 20), with an average cost of $5/tonne. Perhaps more importantly, the very high costs on the right tail of the
distribution are characteristic of regions which otherwise might be considered good injection zones, i.e. regions with high permeability. The distributions shown in Figure 20 make it clear that these two criteria for well spacing do not yield similar results for cost of distribution estimations. The average well spacing with the interference method is 30 km, which means that each well has a footprint of nearly 1000 square kilometers.

![Distribution of Costs](image)

**Figure 20:** Distribution of Cost for Spacing Criteria. A Monte Carlo Simulation of 100,000 sets of geological properties drawn from uniform distributions across a range of geological conditions evaluated for their distribution costs are represented here. Each set of properties was analyzed to determine injection rate and well spacing under capacity based spacing (blue) and interference-based spacing (green).

Unfortunately, there is relatively little geological data to put these calculations in context, but we can use several injection sites around the world to demonstrate what these numbers might be under real-world conditions. We calculate the distribution costs and footprints of several commercial-scale injection scenarios (1, 10, and 100 Mt/year) for four representative sites: Sleipner West, with high permeability and a
relatively thick injection layer, the Frio injection project, with a relatively thin layer and moderate permeability, the Mt. Simon, which has no CO₂ storage projects at the injection stage but is a good example of a very thick injection layer with several regions of low permeability, and the Nagaoka injection project, which is a marginal reservoir with low thickness and low permeability. The calculations are performed with reported injection rates, layer thicknesses, permeabilities, and depths (from which temperature, pressure, and porosity are calculated) (Bureau of Economic Geology (BEG) 2000; Eccles et al. 2009). These are intended to be representative of combinations of real-world conditions and not necessarily predictions for performance at any of these sites.

The results, shown in Table 4, illustrate several important conclusions. First, that as expected, the capacity model and interference model for well spacing can produce very different footprint and cost estimates. Despite the low variance in the Monte Carlo simulation for the capacity estimate, we see a very broad distribution of costs among the sites for the capacity method, ranging over three orders of magnitude from $0.20 to over $25 per tonne. This reflects the fact that although the capacity method often yields well spacings that are relatively low, in thin layers with poor permeability (such as Nagaoka), the number of wells required and the low bulk volume of the reservoir combine to produce very high distribution costs. On the other hand, the Mt. Simon, with its vast bulk volume and likely high injection rate (due to high net sand thickness), needs a very small footprint per well and very few wells.
### Table 4: Distribution system for representative sites at commercial scales

<table>
<thead>
<tr>
<th>Site</th>
<th>Capacity Model</th>
<th>Interference Model</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Capacity Model</td>
<td>Interference Model</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Distribution Cost</td>
<td>Footprint sq. km</td>
<td>Distribution Cost</td>
</tr>
<tr>
<td></td>
<td>2010 USD/tonne</td>
<td>2010 USD/tonne</td>
<td></td>
</tr>
<tr>
<td>Sleipner</td>
<td>1 Mt/y $0.49 17</td>
<td>$4.33 1288</td>
<td></td>
</tr>
<tr>
<td></td>
<td>10 Mt/y $0.32 170</td>
<td>$2.80 12883</td>
<td></td>
</tr>
<tr>
<td></td>
<td>100 Mt/y $0.33 1700</td>
<td>$2.91 128832</td>
<td></td>
</tr>
<tr>
<td>Frio</td>
<td>1 Mt/y $7.91 2389</td>
<td>$5.68 1232</td>
<td></td>
</tr>
<tr>
<td></td>
<td>10 Mt/y $5.60 23893</td>
<td>$4.02 12317</td>
<td></td>
</tr>
<tr>
<td></td>
<td>100 Mt/y $6.67 238927</td>
<td>$4.79 123175</td>
<td></td>
</tr>
<tr>
<td>Mt Simon</td>
<td>1 Mt/y $0.31 6</td>
<td>$0.46 15</td>
<td></td>
</tr>
<tr>
<td></td>
<td>10 Mt/y $0.20 63</td>
<td>$0.30 145</td>
<td></td>
</tr>
<tr>
<td></td>
<td>100 Mt/y $0.21 635</td>
<td>$0.31 1453</td>
<td></td>
</tr>
<tr>
<td>Nagaoka</td>
<td>1 Mt/y $26.46 7301</td>
<td>$5.28 291</td>
<td></td>
</tr>
<tr>
<td></td>
<td>10 Mt/y $22.19 73012</td>
<td>$4.43 2911</td>
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<tr>
<td></td>
<td>100 Mt/y $24.69 730117</td>
<td>$4.93 29111</td>
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By contrast, the interference method appears to have extremely low variance. This is because the two factors in distribution costs (injection rate/number of wells and well spacing) have opposite effects on cost. High permeabilities mean that wells will interfere with each other to a higher degree, but also that wells will have high injection rates. Either way, costs will be relatively high (approximately $4 per tonne), but the
costs will never be prohibitively expensive. Random sampling from distributions of properties is not likely to be representative of real-world conditions given the correlations between these properties.

The site footprint calculations are intriguing as well. Using the capacity model, it is quite clear that relatively thick formations will have low footprints, as one might imagine from basic bulk volume calculations. This is not particularly surprising, and although the footprint for the thin injection layers stray into the unrealistic realm (a site of 100 Mt/y injecting in a Nagaoka-type layer would require a footprint slightly larger than the area of the state of Texas), we find reasonable estimates of tens or hundreds of square kilometers for Sleipner- or Mt Simon-like sites.

However, under the interference model, these two reservoirs are extremely different in the footprint they would require. The area required by the Sleipner field increases by nearly a factor of ten, whereas it only doubles in the case of the Mt. Simon. This is because both sites have a high injectivity for different reasons: the Mt Simon has a low permeability but thick injection zone to compensate, whereas the Utsira Sand at Sleipner West has a very high permeability. If the interference model is correct, the Mt Simon could inject the emissions of a 500 MW power plant in under 100 square kilometers, whereas a Sleipner-type reservoir would have to be several thousand square kilometers (roughly the size of Delaware) for the same annual capacity.

These results show an intriguing and heretofore unexpected criterion for evaluating sequestration sites: low permeability. This is, in fact, counterintuitive, because for the most part, high permeability means higher injectivity, an important factor in decreasing cost of injection(Eccles et al. 2009). However, low permeability means that wells will have low interference, and the loss of injectivity can be overcome if
the injection layer is sufficiently thick (Eccles et al. 2009), demonstrated with the horizontal injection wells at the in Salah gas field (Riddiford et al. 2007). The Mt. Simon may be a perfect example of this, as Table 4 illustrates; its costs and footprints are low under both criteria and alone among the representative sites would be ideal for sequestration under any condition presented in this paper. We conclude that low permeability (paired with high injection zone thickness) should be an important criterion for geosequestration site selection. Illustrated in Figure 21, these site selection criteria are counterintuitive according to convention but obvious in retrospect once pressure interference is taken into account.

Figure 21: Illustration of Site Selection Criteria. Based on our results, we find that although traditionally a site with high permeability and high thickness would be the best sequestration site, the best injection sites will actually be those with high thickness and low permeability (See Table 2).
4.4. Discussion

Our results indicate that there is still a great deal of uncertainty regarding the cost of geosequestration. Over the range of geological characteristics we analyzed, all of which can be found in potential sequestration sites (Bureau of Economic Geology (BEG) 2000; Hovorka et al. 2001; Eccles et al. 2009), costs range from negligible to preclusive. This is similar to the conclusions regarding injection cost in Eccles et al, which found costs ranging over several orders of magnitude for drilling and injection alone (Eccles et al. 2009). If sites can be identified with the requisite characteristics for low cost distribution (i.e. high injection rate and low well spacing) and a realistic site footprint, these reservoirs will make geosequestration and the entire CCS system an attractive option compared to other methods for abating GHG emissions. We find that low permeability paired with high injection layer thickness are the necessary criteria for these conditions (see Fig 21).

Geological variability is therefore important in evaluating the total cost of geosequestration and more specifically the distribution pipeline component of cost. Unfortunately, the spatial extent and sampling density of datasets that include the necessary parameters, such as permeability, is not very good outside a few major aquifers (Bureau of Economic Geology (BEG) 2000). Subsequent efforts to gather data have focused on determining capacity and have not collected the critical parameter of permeability, necessary to determine injection rate and potentially well spacing (Department of Energy (DOE) 2010). Without such data, it is difficult to estimate the true distribution of costs CCS operators are likely to encounter for distribution of CO2 within a sequestration site and the total footprint required for commercial-scale sites.
Our analysis does indicate that distribution costs are not likely to be negligible, however. Of the two methods for evaluating well spacing, we believe that the well interference method is more likely to be representative of reality, although obviously the physical bulk volume requirements would take precedence if they were larger. When CO$_2$ sequestration was first considered in literature, the effects of injection on reservoir pressure and the implications for storage capacity were discussed (L.G.H. van der Meer 1993; L. G. H. van der Meer 1995), but for the most discarded until recently (Lubertus van der Meer & van Wees 2006; Bert van der Meer & Egberts 2008; Nicot 2008; Birkholzer et al. 2009; Birkholzer & Q. Zhou 2009). The alternative, based on volumetric calculations and capacity factors, is dependent on the assumptions or calculations of the capacity factors. These capacity factors, as Bachu et al point out, are poorly understood and require site-specific evaluation (Stefan Bachu et al. 2007). Although a range has been proposed in literature (Birkholzer & Q. Zhou 2009), these are based on limited field site experiments or numerical simulations without considering multiwell injector systems (Doughty et al. 2001; Hovorka et al. 2001). These capacity factors are almost certainly largely accurate for plume evolution evaluation from a single well, but it is not appropriate to use them for multi-well injection systems. Van der Meer et al point out the importance of considering basin-scale impacts of injection (Bert van der Meer & Egberts 2008; Bert van der Meer & Yavuz 2009), absent from these calculations of capacity factor.

Beyond the tentative nature of capacity factor calculations, it is clear from our calculations with the Theis solution that if a site operator were to try to use a capacity method for well spacing, the injection wells would simply be unable to perform correctly as pressure interference builds. Operators are no doubt free to attempt this,
but it is likely that they would see major reductions in well performance as a result. The
contraction in well spacing would have to be balanced by the expansion of the site,
including drilling new wells, site evaluation, and distribution to compensate. In
practical terms, the cost of such a site would approach the interference criterion cost,
with the added stranded capital of underperforming wells. Since our calculations are
made with the fracturing pressure constraint, it is unlikely that operators would be able
to increase the injection pressure to compensate for this interference. However, it is
possible that in high-injectivity regions that are limited by engineering performance (i.e.
pump flow rate as opposed to fracturing pressure), the interference problem may not
severely impact performance.

Because of these reasons, we believe that the interference criterion is a better way
to evaluate well spacing and cost. Operators will be able to select (or optimize) the
degree to which they will tolerate well interference and space the wells accordingly;
although this will not allow them to completely utilize the volumetric capacity of the
reservoir, it will be a more appropriate estimate of cost for distribution than the capacity
criterion. We note, however, that if the capacity model leads to an estimate of well
spacing that is higher than the interference model, the larger of the two should be used,
as the injector wells may not interfere with each other but may not actually have the
void space available to store CO$_2$ over the lifetime of the project.

Along the lines of research by Birkholzer et al (Q. Zhou et al. 2008; Birkholzer et
al. 2009; Birkholzer & Q. Zhou 2009), van der Meer et al (Lubertus van der Meer & van
Wees 2006; Bert van der Meer & Egberts 2008; Bert van der Meer & Yavuz 2009), and
others (Nicot 2008), reservoir pressure management must be taken into account in
capacity estimates, including the use of capacity factors in volumetric storage capacity
calculations. Capacity factors in the range of 1-4% are almost certainly too high when considering these pressure implications, and as a result many modern storage capacity assessments and methodologies might need to be revised (Department of Energy (DOE) 2010; R Burruss et al. 2009).

Numerical simulations of void space utilization that result in capacity factors in the range of 4% such as those by Doughty et al. (2001) and the even higher ranges employed in the USDOE’s capacity evaluation in the NATCARB project (Department of Energy (DOE) 2010) might certainly be accurate for the performance of a single well and presumably also accurate for plume evolution even in multi-well systems, but our work indicates that since the wells communicate pressure well beyond the actual migration front of the injected CO₂, storage sites must work with an effective capacity factor that is much lower than the pore space utilization. For example, if our capacity model evaluates a 4% capacity factor leading to an average of 5 km between wells, the fact that the interference model produces an average minimum well spacing of 30 km indicates that the effective utilization of pore space for this distribution of properties is approximately 0.11%, much lower and notably closer to that reported in early work on pressure management by van der Meer (1995). Using such a figure as an average as though it were from a normal distribution (as is the practice for the NATCARB evaluations, for example (Department of Energy (DOE) 2010)) would be highly misleading, however, as indicated by the results shown in Table 2. In regions with high permeability, similar to that found in the Utsira sand at Sleipner West, the effective capacity factor should be revised downward dramatically to as low as 0.05%, but for reservoirs with low or moderate permeability, the effective capacity factor is not impacted at all or, in the case of our hypothetical Mt. Simon site, is revised downward to
only 1.75%, a very reasonable value that would not significantly affect capacity estimates previously made of the Mt Simon Sandstone. This indicates that it is impossible to accurately gauge the sequestration capacity potential of a formation without measuring its permeability. This particular conclusion has important implications for policymakers and potential CCS operators, as the total mitigation potential of CCS plays an important role in determining its deployment relative to alternative GHG emissions abatement options.

Another factor that will affect the deployment of CCS is the scale of the distribution system. A 100 Mt/y site seems very large, but it would sequester only 4% of current electric power sector CO2 emissions and less than 2% of current total U.S. emissions (EIA 2009). At the same time, it is difficult to imagine that such a site would have a footprint of much less than 1000 sq km. On the scale of the total area of the United States, this may be relatively small, but when dealing with the scale of private property and mineral rights, this is extremely large. By comparison, only 3% of US farms are larger than 8 sq km (United States Department of Agriculture (USDA) 2010). In Texas, where the population density is very slightly above the US average (US Census Bureau 2000), a footprint of a thousand square kilometers would impact nearly 37,000 people, many of whom might hold property or mineral rights and all of whom would be stakeholders. Beyond the coordination of CO2 disposal under such a large area, the implications for compensating property owners may be quite large under such scenarios (Gresham et al. 2010). It is also extremely unlikely that the geological environment would be homogeneous enough to support injection in such massive sites; even moderate total injection rates in high-permeability regions still have extremely unrealistic footprints when geological variation in properties such as cap rock integrity
is considered (Bureau of Economic Geology (BEG) 2000). Again, we conclude that low permeability reservoirs will be the best in terms of their footprint and expect that selection of such reservoirs would minimize the total footprint of the CCS system as a whole. Nonetheless, the size of any substantial effort to mitigate carbon emissions through CCS will be enormous even under the best of circumstances.

Finally, we believe that the cost of distribution may be an extremely important factor to consider when performing economic evaluations of the CCS system. Our results demonstrate that relatively thin reservoirs, whether they have good permeability or not, will have extremely high distribution costs even if they have sufficient bulk volume to sequester a substantial amount of CO2. Such reservoirs, unlikely candidates to begin with, should not be included in realistic capacity evaluations that move beyond physical potential and into economic or social constraints. Furthermore, the variation in distribution costs for good reservoirs (i.e. those with high injectivity and bulk volume) with the interference model is roughly on the order of that estimated for injection costs (Dooley et al. 2004; Middleton & Bielicki 2009; Eccles et al. 2009). Reservoirs that heretofore may have been ranked in cost based on injectivity (e.g. Sleipner West is better than the Mt. Simon) might find their relative costs now equal or even reversed when the surprising inverse correlation between distribution cost and permeability is taken into account. Since these costs vary unexpectedly across potential reservoirs, transport models that match sources and sinks (e.g. Dooley et al(2004), Dahowksi et al(2009), Wildenborg et al(2004), Middleton and Bielicki(2009), McCoy and Rubin(2008a)) might both inaccurately assign sources to sinks and incorrectly estimate the average or total costs of the transport and storage components of CCS.
5. Global Ocean Storage Potential in Self-Sealing Marine Strata

5.1. Introduction

Climate change threatens to increase average global temperature, raise sea level, and alter weather patterns in ways that could harm natural ecosystems and affect human civilization (Bernstein et al. 2007). The root cause for climate change is anthropogenic greenhouse gas (GHG) emissions, which are increasing the heat-trapping capacity of the atmosphere. A majority of scientists concur that to avoid many of the negative impacts anticipated to arise from global warming, GHG emissions will need to be significantly reduced or eliminated over the next century (Bernstein et al. 2007).

One option for mitigating GHG emissions is carbon capture and storage (CCS) (IPCC 2005); CO$_2$ emissions from major industrial point sources, such as power plants, would be captured and transported to sites where the CO$_2$ would then be pumped into large reservoirs for long-term storage. Candidate reservoirs include geologic strata (e.g., deep-saline aquifers, oil/gas reservoirs, and unmineable coals seams) and the ocean (IPCC 2005; Koide et al. 1997). CO$_2$ is currently being stored in the ocean naturally, both through diffusion into surface waters and through uptake by marine biologic productivity. However, the rate of CO$_2$ absorption by the ocean may be slowing due to surface water saturation and acidification (Le Quere et al. 2007; Bacastow R.B. & Dewey R.K. 1996). In CCS, ocean storage would involve the injection of CO$_2$ into the water column at intermediate depths for dissolution (500-1500m), or at deep depths (>3000m) where the injection plume would become negatively buoyant, sink and pool upon the seafloor (E. Eric Adams & Caldeira 2008). The CO$_2$ could also be injected into strata beneath the seafloor (IPCC 2005; House et al. 2006).
Schrag argues that sequestration beneath the seafloor may offer the best option for large-scale storage of industrial CO$_2$ emissions because it would avoid potential hazards from direct ocean injection, including harming ocean ecosystems, while also avoiding challenges/risks posed by onshore geologic sequestration (Schrag 2009). The latter include (a) the need for the onshore reservoirs to be isolated within sufficiently large and/or numerous geologic traps that they can safely secure significant quantities of CO$_2$ underground, (b) management of reservoir pressure during CO$_2$ injection to prevent problematic changes to CO$_2$ migration, (c) extensive monitoring of the reservoir for unacceptable levels of leakage, (d) possible groundwater contamination by the CO$_2$ (or by contaminants the CO$_2$ leaches from the reservoir rock), (e) invasion of freshwater aquifers by saline pore waters displaced by injected CO$_2$, (f) uncertain legal and regulatory regimes surrounding subsurface storage of CO$_2$, and (g) likely opposition from land or mineral-rights owners above the storage sites (Schrag 2009). Though sub-seafloor storage of CO$_2$ would also require a secure trap, it would not threaten groundwater, it would move the storage away human habitation, and where done in federal waters (e.g., generally >5 km from shore in the U.S.) would fall under federal regulation and be managed by government agencies that already oversee offshore oil and gas extraction (Schrag 2009).

There are at least three forms of sub-seafloor storage. One is analogous to onshore geologic storage of CO$_2$ in deep saline aquifers (Fig. 22), and is already being demonstrated by Statoil at its offshore Sleipner West and Snøhvit natural gas fields (Michael et al. 2009). CO$_2$ mixed with the natural gas being produced from these fields is separated out at the surface and then pumped back down into saline sandstone aquifers that are disconnected from the fields and capped by thick layers of gas-tight muds.
Figure 22: Schematic Representation of Ocean Storage. In this diagram, several possible forms of ocean storage (represented as green areas) are shown, including sequestration in ocean sediments below a secure cap rock (shown as CO2 below a black line) or potentially below the Hydrate Formation Zone (HFZ). Sinking plume storage from direct ocean injection is also shown in the Negative Buoyancy Zone (NBZ). Finally, the self sealing storage mechanism is illustrated with the circulation that keeps the CO2 trapped. Ocean injection at intermediate water depths or other forms of storage are not shown, nor are regions above the seafloor that might be conducive to hydrate formation.

The second type of sub-seafloor storage is one that could be implemented along the eastern U.S. continental shelf directly beneath layers of basalt that are embedded within the shelf strata (Goldberg et al. 2010). Porous sands in contact with the base of the overlying basalts are attractive reservoirs because injected CO2 would react with the mafic minerals in the basalts to produce non-toxic, void-filling carbonate minerals. Such mineralization would be the most stable and permanent form of carbon sequestration, however, it would also be the slowest. Estimates are that it could take $10^3$-$10^4$y to mineralize a fraction of the CO2 stored in or beneath basalts (Goldberg et al. 2008). Storage of the remaining gaseous CO2 as well as any CO2 dissolved in the pore waters would require other geologic trapping mechanisms. In the case of the Central Atlantic
magmatic basalt province, these additional traps are presumed to be the basalt layers themselves and overlying low permeability sediments (Goldberg et al. 2010).

The third type of sub-seafloor storage and the one we focus on in this paper is that proposed by House et al (2006). They recommend injecting CO₂ into marine sedimentary strata that meets two criteria. The first is that the strata are in deep enough water that the CO₂ would become negatively buoyant under the ocean pressures and temperatures (Fig. 2). The second is that the level of injection in the strata is below the zone at which CO₂ would combine with water to crystallize into a hydrate (Fig. 2). Under the first condition, CO₂ would be denser than the overlying pore fluid and so would remain in place unless entrained by pore fluid flow being driven by thermal gradients or some other mechanism (House et al. 2006). Under the second criterion, any CO₂ that did rise through the strata into the hydrate formation zone (HFZ) would crystallize and form a permeability barrier in the sediments (House et al. 2006), impeding further upward flow of CO₂ in the same way that methane hydrates are trapping methane gas beneath them in shallow marine sediments along continental slopes throughout the world (Milkov 2004).

We refer to marine strata that meet these two criteria as “self sealing”. They are potentially attractive reservoirs for storing CO₂ because the storage is geochemically stable, the conditions for it are predictable, and the strata should be widespread throughout the ocean. As House et al. point out, the gravitational stability of CO₂ beneath the deep-ocean seafloor ensures that the CO₂ will not by itself migrate up fractures in the strata nor be released by earthquakes or other large geomechanical disturbances (2006). As a result, a broader range of marine sediments are likely to meet the pressure-temperature criteria for geochemical trapping of CO₂ than strata with
suitably large yet secure structural and/or stratigraphic traps. House et al. attempt to illustrate this by showing the areal extent of the seafloor with in the U.S. Exclusive Economic Zone (EEZ) where water depth exceeds 3000m, the approximate depth below which CO₂ is negatively buoyant (House et al. 2006).

Here we improve upon this initial mapping by House et al. in order to estimate the global storage potential of self-sealing marine strata and map their worldwide distribution. We do this using global oceanographic datasets for bathymetry (Amante & Eakins 2009), seafloor ocean temperature (Boyer et al. 2009), and sediment thickness (Divins 2010). In our analysis, we first map out the extent of the negative buoyancy zone (NBZ) for CO₂ in the world’s oceans. We then map out the distribution and thicknesses of marine strata in which CO₂ could be stored as a supercritical fluid below the HFZ. The overlap between these two criteria yields our map of self-sealing marine strata. Finally, we constrain the bulk storage capacity of these strata and place its distribution with in the context of the Exclusive Economic Zones of the four largest CO₂-emitting economies: the U.S., China, India and the E.U.

5.2. Methods

We map the NBZ for CO₂ based on the pressure and temperature at the seafloor. Seafloor depths worldwide are derived from global bathymetry data gridded at a horizontal resolution of 10’x10’. Seafloor pressure at each point in the grid is calculated assuming hydrostatic conditions and a constant ocean water density of 1030 kg/m³. This is a conservative value for density over the range of depths we investigate (Boyer et al. 2009) but one that safeguards against overestimating storage potential.
The seafloor temperature corresponding to each point in the bathymetry grid is determined by box-averaging the seafloor temperatures in the World Ocean Dataset (Boyer et al. 2009). The resulting derivative grids of seafloor pressure and temperature are then used in the equations of state for CO$_2$ (Span & Wagner 1996) to generate a corresponding grid of CO$_2$ density at the seafloor. This grid is filtered for CO$_2$ densities greater than 1040 kg/m$^3$ to produce a map of where CO$_2$ would be denser than the surrounding seawater and potentially form a hydrate, sinking to the seafloor.

We map where CO$_2$ could be stored in marine sedimentary strata using the gridded global bathymetry data and the global grid of marine sediment thickness. The bathymetry data are used to estimate the sub-seafloor depth at which pressure exceeds 7.1 MPa and temperature is greater than 31.1°C. This is the critical pressure-temperature point beyond which CO$_2$ becomes a supercritical fluid and would not form a hydrate (Span & Wagner 1996), so the sub-seafloor depth of this point occurs below the HFZ.

The pressure calculations are done as before assuming hydrostatic conditions and a constant density of 1030 kg/m$^3$, in this case for the saline pore waters. The temperature calculations are based on a geothermal gradient of 45.6°C/km, which is the average gradient for wells drilled into marine sedimentary strata by the Ocean Drilling Program that are georeferenced in the National Geophysical Data Center (NGDC) database (World Data Center for Marine Geology and Geophysics 2000a; World Data Center for Marine Geology and Geophysics 2000b). We note that some of these wells have geothermal gradients as low as 20°C/km while others have gradients of over 100°C/km, which could mean our thickness estimates are off by several hundred meters in these outlier areas. However, the ODP wells are too sparsely distributed to interpolate spatial variations in the gradient, which is why we rely on the average.
Following the conservative approach of House et al., we take the deeper of the temperature and pressure thresholds as the depth at which CO$_2$ would transition to a supercritical fluid (2006). We then use the gridded data of world ocean sediment thickness to determine how much sediment, if any lies, below this depth.

Finally, we combine our map of the NBZ for CO$_2$ with our map of sediment thickness below the HFZ to produce a third map of strata thickness that meets both criteria. These are the self-sealing strata.

5.3. Results

Figure 23 shows the global map of the NBZ for CO$_2$. For the most part, the zone lies below the 3000 m depth contour as House et al (House et al. 2006; Goldberg et al. 2008) concluded in their general analysis. We find that the NBZ constitutes a collective area of >282Mkm$^2$ or about 78% of the seafloor. Note that 102Mkm$^2$ of the NBZ coincides with the red clay regions of the ocean, where bottom currents are slow to negligible (1-2 cm/s) (Stow et al. 2002) and at least at present would be unlikely to advect CO$_2$ back up into the water column. At 29 Gt/y (EIA 2009), current global emissions of CO$_2$ could be injected onto the seafloor within the NBZ for >3000y before rising to a uniform fluid thickness of 1m above the seafloor. Importantly, the breadth of the NBZ does not appear to be sensitive to changes in ocean bottom temperatures on the order expected from climate change. For example, if bottom waters were to warm by 2.5°C (Bernstein et al. 2007), the NBZ would shrink by only 4.4%. However as Schrag (Schrag 2009) and others (House et al. 2006; Auerbach et al. 1997; Ishimatsu et al. 2004; Rygg et al. 2009) have noted, simply storing CO$_2$ on the seafloor is not safe; risks range from possible ecologic damage to the benthic environment to unanticipated ocean
motions or disturbances that could carry CO₂ into shallower waters where it could harm other ecosystems or even re-gasify and bubble out of the ocean.

![Figure 23: Direct Injection Potential](image)

Figure 23: Direct Injection Potential: This map illustrates the global ocean storage potential for direct ocean injection in the sinking plume region. The regions in which CO₂ injected at the ocean floor would be more dense than the surrounding seawater (or form hydrates) are outlined in black, with ocean sediment type illustrated as colored shading. In red clay regions, the ocean currents at the seafloor are likely not strong enough to transport the CO₂ from the site of injection. The EEZ’s of major economies are also shown, as are global CO₂ point sources.

These risks would be mitigated if instead the CO₂ were injected into sedimentary strata below the seafloor. Figure 24 is a map of the thickness of marine sediments below the HFZ where CO₂ could be stored as a supercritical fluid. The figure is analogous to maps of CO₂ storage capacity in onshore strata based on their depth of burial and bulk volume (e.g., sandstone saline aquifers (Department of Energy (DOE) 2010)). As with these onshore maps, our offshore map of available sediment thickness provides only a first-order assessment of the sub-seafloor storage potential, for these offshore strata similarly include low-porosity and/or low-permeability layers into which the injection of fluids is not feasible (Stefan Bachu 2003).
Figure 24: Ocean Geosequestration Potential: The thickness of sediment layers in which CO2 would be in a supercritical form below the HFZ is shown, with very thick layers (>2500m) in green and relatively thin layers (<500m) in red. Storage of this type, as on land, would be restricted to sediment layers with high injectivity (such as permeable sandstones) below a trapping mechanism, such as an impermeable cap rock. The EEZ’s of major economies are also shown, as are global CO2 point sources.

Globally, 108M km$^3$ of ocean strata meet the conditions for keeping CO$_2$ in a dense, supercritical form below the HFZ. The storage potential of onshore strata is calculated by the USDOE assuming that only 20-80% of the strata possess sufficient cap rock integrity to hold the CO2, which puts the total capacity factor (or the fraction of pore space in a formation that CO2 might physically occupy) at just 0.5-5.5% (Department of Energy (DOE) 2010). Applying these same standards to the offshore strata and assuming a pessimistic 10% for average porosity (Goldberg & Slagle 2009), the available offshore strata could store hundreds of thousands of gigatonnes of CO$_2$, or many centuries worth of current global emissions.

Not surprisingly, the majority of these offshore strata are found along continental margins (Fig 24) where sediments accumulations are thickest and the thermal gradient is
favorable to keeping CO₂ in a supercritical state starting at relatively shallow sub-seafloor depths. However, half of these strata lie above the NBZ for CO₂ (Fig 22). This shallower fraction of the offshore strata is similar to onshore storage sites in that CO₂ could only be housed safely where the strata possess geologic traps sealed by cap rocks as in the case of the Sleipner West and Snovhit injection projects (Michael et al. 2009). Such locations would also likely have to be monitored for leakage, a challenge that could end up being more difficult than monitoring geologic sequestration on land (Qi Li et al. 2009).

As discussed, the most promising deep offshore sequestration resource may be the self-sealing sedimentary strata. Figure 25 shows the extensive regions in the ocean where these strata occur. Assuming the same 0.5-5.5% sweep efficiency and 10% porosity as before, an onshore reservoir of this scale would have a bulk storage volume of ~50M km³ and could potentially hold >100,000 GtCO₂. Again, because these offshore strata do not require additional geologic traps, a good portion of this potential capacity might be utilized.

Access to the self-sealing strata for different nations, however, is not uniform. We have used the IEA database of global CO₂ point sources (International Energy Agency Greenhouse Gas R&D Programme 2002) to calculate the Euclidean distance from each available source location to the closest site where CO₂ could be disposed of in self-sealing strata. We have compiled our results for the world as well as for the sources in the four largest CO₂ emitting economies: China, India, the U.S. and the E.U. Approximately 12 billion tonnes of global CO₂ emissions are emitted by the point sources in this database that include geocoordinates; another 2 billion tonnes are listed but cannot be mapped (of which over 1 Gt are emitted in China). The results are shown
in Figure 26 ordered by distance and plotted as a cumulative emissions curve in a manner similar to the cost curves constructed for North America by Dooley et al (2004), for China by Dahowski et al (2009), and for Europe by Wildenborg et al (2004), with cost replaced by distance in our plot.

Figure 25: Self-Sealing Potential: Sediment layers that lie below a sinking plume region would be able to store CO2 permanently because of density-driven circulation and hydrate formation above the depth of injection. In this map, we show the thickness of sediment layers available at these depths below the sinking plume regions. Storage would require sediment layers with high injectivity, but not an impermeable cap rock. The Exclusive Economic Zones of the United States, the European Union, China, and India are shown, as are global CO2 point sources.

Our cumulative emissions curve (Fig. 26) shows that almost 10Bt CO2 out of the 12Bt CO2 emitted annually from all the point sources analyzed, or roughly a third of global CO2 emissions, are within 1,000 km of self-sealing strata; 4.5Bt CO2 are emitted within 500 km, 1.5Bt CO2 within 200 km, and nearly 500Mt CO2 within 100 km. Of the major economies (Fig 26b), India has the best initial access to self-sealing strata, with almost 200Mt CO2 (15%) of its annual releases being within 100 km of such strata(EIA 2009). The EU and China, by contrast, release only 250Mt (6%) and 330Mt (6%) of their
respective CO$_2$ emissions within 500 km of the strata. Within this same distance, the U.S. releases 1Bt CO$_2$ /y (16%) and India 800Mt CO$_2$ /y (62%) (EIA 2009).

Figure 26: Cumulative Emissions Curve: The cumulative emissions at or below a given distance from the self-sealing geological storage region are shown for the (a) the globe and (b) the United States, China, India, and the European Union. Both distance to the nearest self-sealing region (solid line) and to the nearest self-sealing region within the EEZ (dotted line) are shown in (b). India and the U.S. have sources considerably closer to the nearest sinking plume region compared with the EU and China, for the most part. Over 2 GT of global point source emissions, more that 1 GT of which are in China, are not shown, as they have no geospatial data available.
5.4. Discussion and Conclusions

Our map of self-sealing marine sedimentary strata significantly improves upon the first attempt to illustrate the possible extent of these strata by House et al. (House et al. 2006), which they did using only the bathymetry of the U.S. EEZ. Our map is derived from a more rigorous estimation of CO$_2$ density, is global, and includes an assessment of the thickness in addition to the location of strata where CO$_2$ might safely be stored.

As previously pointed out, however, only a small fraction of these strata may be capable of storing CO$_2$. This is because even though we show that the combination of geochemical trapping mechanisms is widespread in marine sediments, particularly along continental margins, self-sealing marine strata will only be effective in helping mitigate climate change if they contain reservoirs of sufficient porosity and permeability as to be able to handle the annual injection of megatonnes of CO$_2$ over a period of decades. In short, the self-sealing strata will need to contain relatively thick and extensive layers of sandstone, an attribute our mapping does not address. These sand bodies do exist, however, as attested to by recent deepwater discoveries offshore in the U.S. Gulf of Mexico (e.g., Thunder Horse and Perdido Fields) and Brazil (e.g., Tupi and Jupiter fields) of sandstone reservoirs that could contain billions of barrels of oil (Ray et al. 2004; Brainard & Martinez-Diaz 2009; Fiduk et al. 1999; Geologists 2003). Additionally, our conservative estimate of the total storage potential within self-sealing marine strata indicates that even if only a fraction of a percent of the total volume of these strata could store CO$_2$, the capacity would still be orders of magnitude larger than current annual global emissions. This capacity (>100,000 Gt) is ten times or more greater than the majority of estimates for the global capacity of major types of onshore geologic
reservoirs (i.e. deep-saline aquifers, oil and gas reservoirs, and unmineable coal seams), which for the most part range from 1000-10,000 Gt (John Bradshaw et al. 2007).

Thus, the self-sealing marine strata appear to be a significant potential resource for disposing of CO$_2$ emissions. Whether these strata are also a technically and economically viable resource though remains to be established. A number of technical requirements could lead to total costs for CO$_2$ transport and storage that are significantly higher than those currently estimated for storage in onshore reservoirs. These requirements include an extensive offshore pipeline system, possibly in combination with liquefied gas tankers, to transport the supercritical CO$_2$ into water depths >3000m. And at these depths, it appears that insulated pipes may be needed to prevent the CO$_2$ from forming hydrates and blocking further flow before it is pumped beneath the seafloor (House et al., 2006).

Nonetheless, the unresolved legal, societal and management issues associated with onshore storage summarized by Schrag (2009), could still end up making offshore storage a more attractive option. For example, the decreased technical, social, and political risks of leakage from CO$_2$ stored in self-sealing marine strata could result in fewer stringent requirements for site characterization. This characterization may also be speeded up and thus made less costly by the fact that pressure and temperature measurements are all that is needed to identify where the combination of geochemical trapping mechanisms exist. While this form of trapping may not totally eliminate the need to monitor for leakage, it might simplify it, since temperature and pressure regimes and not impermeable cap rocks would be responsible for trapping.

The risks associated with storing CO$_2$ in self-sealing marine strata parallel those of proposals to geoengineer the climate to counteract the global warming effects of
GHGs (Keith 2000; Schneider 2001). Both approaches could help stabilize climate even as
the world continues to predominantly rely on fossil fuels for energy, but both could also
create unintended and potentially threatening environmental problems of their own
(Robock 2008; McKibben 2006). As the recent oil spill in the Gulf of Mexico shows,
there are risks associated with underwater drilling that may have significant
consequences, and even self-sealing storage is unlikely to be immune from all possible
modes of failure. With properly established safeguards, however, offshore injection into
self-sealing strata could obviate many of the risks associated not only with offshore but
also onshore sequestration.

Like deep saline aquifers onshore (Department of Energy (DOE) 2010), self-
sealing marine strata could be a significant resource for storing CO$_2$ emissions from
large point sources that employ CCS. The United States and India in particular appear to
have good access to self-sealing strata, but China and the European Union may not be
able to utilize this opportunity as easily. Studies of onshore sequestration have shown
that the spatial distribution and quality of potential CO$_2$ reservoirs can impact not only
the cost of CCS and in turn its market penetration, but also the configuration of the
transport and storage components of such systems (Dooley et al. 2004; Dahowski et al.
2009; Middleton & Bielicki 2009). Our maps of self-sealing strata provide nations with
additional information for broadening their national-scale assessments of storage
potential to include their EEZs in evaluating the feasibility of CCS as a climate
mitigation strategy.
Appendix A

A1. Model Parameters

For the purposes of this analysis there are four categories of parameters used as inputs. First, there are properties that are constant, which include the acceleration of gravity, the compressibility of water and the temperature, pressure, and density of CO$_2$ as it enters the supercritical state. Second, there are properties relating to the sandstone strata which are meant to be characteristic of all such reservoirs and do not vary widely among basins. These include the shear strength and friction coefficient of sandstone, the density of the overburden material, the exponential decay coefficient of porosity, and the compressibility of the rock skeleton. Third, there are properties which vary generally vary among basins but not to a large degree within basins and are used to compute the upper and lower end members of the range of maximum theoretical effective storage potential and injection rate, which include temperature and density of the pore fluid (and thus hydrostatic pressure and maximum pressure for injection). Finally, there are reservoir properties that are very site (or basin) specific, varying to a high degree among and within basins. These are permeability, layer thickness, and the depth of the reservoir. We evaluate maximum effective storage potential and injection rate as a function of depth between two end-member cases using constant permeability, layer thickness, and actual depth of a reservoir, the values and basis of which are discussed below. We then modify these parameters for site-specific analyses.

The values used in Component 1 (effective storage potential) not noted in the text are those used to calculate porosity. We base our porosity calculations on empirically derived values for the initial porosity at the Earth's surface $\phi_0$ of 0.617 and an exponential decay constant with depth $c_3$ of 5.55*10$^4$ for sands based on porosity measurements in sediment cores from around the world (Bahr et al. 2001).
To evaluate the upper and lower end members of pressure and temperature, we consider two profiles for each regime. For temperature, high and low profiles with depth are those for hot and cold sedimentary basins (i.e., basins situated upon hot or cold lithosphere). We determine these profiles using initial temperatures $T_0$ of 20°C and 10°C and temperature gradients $c_1$ of 45°C/km and 25°C/km, respectively (Nordbotten et al. 2005). We calculate upper and lower hydrostatic pressure profiles for very saline versus fresh pore waters using fluid densities of 1300 kg/m$^3$ and 1000 kg/m$^3$, respectively (Nordbotten et al. 2005). Furthermore, for the saline case, we assume the water tables starts at the Earth’s surface, while for the fresh water case it starts at 200 m so that an even greater range of hydrogeological environments and possible pressures are addressed. This range of water table depth is found in some U.S. basins such as the Denver Basin (U.S. Geological Survey 1995).

The values used in Component 2 (injection rate) not noted in the text are as follows: For the calculation of $P_f$, we used a value of 16 MPa for the shear strength $\tau_s$ and 0.5 for the friction coefficient $\mu$ (Suppe 1985). We derive $\sigma_3$ from the high and low pressures computed from Equation [2]. The value of $\sigma_1$ is the overburden pressure from a column of sandstone with a cumulative bulk density calculated using the porosity curve and the appropriate pore water density (Suppe 1985). The inputs to Equations [8]-[12] included water densities of 1000 kg/m$^3$ and 1300 kg/m$^3$, a rock skeleton compressibility of $2.3\times10^{-10}$ (Turcotte & Schubert 2002), and a pore fluid compressibility of $4.6\times10^{-10}$ (Fetter 2001).

In our sensitivity analysis, we transformed our parameter values for depth, layer thickness, and permeability ($X$) to a scale between $-1$ and 1, plotting these values vs. a multiplication factor for cost. These normalized values ($X^*$) between $-1$ and 1 are on the
X-axis of Figure 6 and the multiplication factor and the cost multiplication factor ($Y^*$) are on the Y-axis. These new values were calculated for depth with

$$X^* = \frac{X - \bar{X}}{\bar{X} - \bar{X}} - 1 \quad [A1]$$

and for permeability and layer thickness with

$$X^* = \frac{\log(X) - \log(\hat{X})}{\log(\hat{X}) - \log(X)} - 1, \quad [A2]$$

where $\hat{X}$ is the maximum value of that parameter. The cost multiplication factor was calculated with

$$Y^* = \frac{Y}{\bar{Y}}, \quad [A3]$$

where $Y$ is the cost of storage and the mean of $Y$ is $2.87$/tonne.

**Table 5: Model Parameters**

<table>
<thead>
<tr>
<th>Description</th>
<th>Variable</th>
<th>Units</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Dependent variable</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Depth</td>
<td>$z$</td>
<td>meters</td>
<td>500, 3000</td>
</tr>
<tr>
<td><strong>Category 1: Constant Values</strong></td>
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<td></td>
<td></td>
</tr>
<tr>
<td>Supercritical CO$_2$</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Temperature</td>
<td>$T_{\text{crit}}$</td>
<td>K</td>
<td>305</td>
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<tr>
<td>Pressure</td>
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<td>MPa</td>
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<tr>
<td>Density</td>
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<td>kg/m$^3$</td>
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</tr>
<tr>
<td>Gravitational Acceleration</td>
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<td>m/sec$^2$</td>
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</tr>
<tr>
<td>Compressibility of Water</td>
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<td>4.60E-10</td>
</tr>
<tr>
<td><strong>Category 2: Sandstone Properties</strong></td>
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<td></td>
<td></td>
</tr>
<tr>
<td>Country Rock</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Density</td>
<td>$\rho_c$</td>
<td>kg/m$^3$</td>
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</tr>
<tr>
<td>Shear Strength</td>
<td>$\Sigma_0$</td>
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<tr>
<td>Friction Coefficient</td>
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<tr>
<td>Compressibility</td>
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<tr>
<td>Surface Porosity</td>
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<tr>
<td>Porosity decay coefficient</td>
<td>$c_3$</td>
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<td>5.55E+04</td>
</tr>
<tr>
<td><strong>Category 3: Low and High End Members</strong></td>
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<td>High</td>
<td></td>
</tr>
<tr>
<td>----------------------------------------</td>
<td>-----</td>
<td>------</td>
<td></td>
</tr>
<tr>
<td>Temperature</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Surface Temperature ( T_0 ) deg C</td>
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<td>10</td>
<td></td>
</tr>
<tr>
<td>Temperature Gradient ( c_1 ) deg C/km</td>
<td>45</td>
<td>25</td>
<td></td>
</tr>
<tr>
<td>Pore Fluid Density ( \rho_w ) kg/m³</td>
<td>1000</td>
<td>1300</td>
<td></td>
</tr>
<tr>
<td>Water Table Depth ( z_0 ) m</td>
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<td>0</td>
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</tr>
<tr>
<td><strong>Category 4: Reservoir Characteristics (Base Case)</strong></td>
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<td></td>
<td></td>
</tr>
<tr>
<td>Layer Thickness ( b ) m</td>
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<td></td>
<td></td>
</tr>
<tr>
<td>Permeability ( k ) md</td>
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<td></td>
<td></td>
</tr>
<tr>
<td>Reference Depth ( z_0 ) m</td>
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<td></td>
<td></td>
</tr>
<tr>
<td><strong>Economic Variables</strong></td>
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<td></td>
<td></td>
</tr>
<tr>
<td>Decision Period ( t ) years</td>
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<td></td>
<td></td>
</tr>
<tr>
<td>Discount Rate ( r ) apr</td>
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<td></td>
<td></td>
</tr>
<tr>
<td>Cost of Drilling</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Fitted Coefficients ( a_1 ) $</td>
<td>4.65E+05</td>
<td></td>
<td></td>
</tr>
<tr>
<td>( b_1 ) $/m</td>
<td>-522.75</td>
<td></td>
<td></td>
</tr>
<tr>
<td>( c_1 ) $/m²</td>
<td>0.28942</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Cost of Injection</td>
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<td></td>
<td></td>
</tr>
<tr>
<td>Fitted Coefficients ( a_2 ) $</td>
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<td></td>
<td></td>
</tr>
<tr>
<td>( b_2 ) $/m</td>
<td>-24.93</td>
<td></td>
<td></td>
</tr>
<tr>
<td>( c_2 ) $/m²</td>
<td>0.01385</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Appendix B

B1 Data Methods

We prepare the data by importing the Bureau of Economic Geology’s GIS data (Bureau of Economic Geology (BEG) 2000) into an ArcGIS database and using it to construct a continuous raster of each geological property of interest in the basins we analyzed. Once each basin’s data is consolidated in a feature dataset in the geodatabase, we develop data models to convert the shapefiles into raster grids at a resolution of 1 km for analysis. Generally, we use one of two approaches to build the necessary raster datasets: interpolation for data that is available and reconstruction for data that is missing.

The two most common data types are topographic line data and sample point data. Line data is interpolated with the native ArcGIS topo to raster tool with no enforcement of drainage. We analyze point data to determine the degree of spatial autocorrelation and then interpolate this data using a kriging method. There are some exceptions; geostatistical analysis to determine spatial autocorrelation requires ten or more data points and some datasets had fewer than ten data points. In those cases a simple inverse-distance weighted interpolation was used. Where the data is in polygon form, we convert the polygon directly to raster. When there are multiple values for all the features in the dataset, we average these values. When there are multiple values for only some of the features, we use the set of values with the most complete spatial coverage. Generally, in the latter case, there was not a large degree of variation among the values for features with multiple values. This tended to occur most often for salinity, with excluding the additional values having almost no impact on the resulting flattened average density raster. Note that we interpolate but do not extrapolate data. The
coverage of the analysis is thus limited by the smallest extent of the input rasters. In some cases, we used data reported as text to produce a dataset (for example, if net sand thickness is reported as 50% of formation thickness, we construct the net sand raster from the thickness raster). Additionally, when the spatial extent of data that could be reconstructed from depth gradients did not correspond to other data (i.e. if there were no regions of the analysis area with complete data, a state which would produce no results at all), we opted to reconstruct those properties rather than use the reported data with limiting spatial extent.

When data is not available (or has problematic extent, as explained above), we use one of two methods to reconstruct the information from other parameters if possible. The first method is using average properties to extrapolate constant values or relationships over an entire basin. Salinity data often had an extremely limited physical extent or did not exist at all; moreover, pore fluid density (the parameter calculated from salinity) rarely varied spatially by more than 3% or so within a basin. We reconstruct this dataset by using the average salinity of the limited spatial dataset for a constant raster over the entire basin or by assuming there were no dissolved solids for a constant density raster, as this assumption led to the most accurate injection rate result in the Eccles et al. model (Eccles et al. 2009). Similarly, we reconstruct net sand thickness in one case as a fixed fraction (0.63) of formation thickness. This fixed fraction was determined by the average value of net sand thickness divided by formation thickness over all the data available.

The second method is to reconstruct a missing dataset using depth-based gradients. We use this to reconstruct temperature, pressure, and porosity where necessary. The relationships used in Eccles et al (Eccles et al. 2009) (themselves derived from other works – linear gradients for temperature (Nordbotten et al. 2005) and
pressure (U.S. Geological Survey 1995) and exponential decay of porosity with depth (Bahr et al. 2001)) to model the changes in these values with depth are implemented here. For a more detailed summary of the methods used to convert the BEG shapefiles into raster data, see Table 5.

**Table 6: Methods for Data Interpolation and Reconstruction**

<table>
<thead>
<tr>
<th>Formation</th>
<th>Data Type</th>
<th>Data Manipulation</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Polygon</td>
<td>Line</td>
</tr>
<tr>
<td>Mt Simon</td>
<td>3</td>
<td>1,2,5,6,7,8</td>
</tr>
<tr>
<td>Frio</td>
<td>1,3,4</td>
<td>2,6,7,8</td>
</tr>
<tr>
<td>Cape Fear</td>
<td>2,4,8</td>
<td>1,3,7</td>
</tr>
<tr>
<td>Lower Potomac</td>
<td>8</td>
<td>1,2</td>
</tr>
<tr>
<td>Glen Canyon</td>
<td>1,2,7,8</td>
<td>3</td>
</tr>
<tr>
<td>Oriskany</td>
<td>4,7,8</td>
<td>1,2,3,5,6</td>
</tr>
<tr>
<td>Paluxy</td>
<td>1,3,4,7</td>
<td>2,6,8</td>
</tr>
<tr>
<td>St Peter</td>
<td>2</td>
<td>1,3,4,7</td>
</tr>
<tr>
<td>Pottsville</td>
<td>2,6</td>
<td>1,2,3,4</td>
</tr>
<tr>
<td>Repetto</td>
<td>2,5,6,7,8</td>
<td>1,3,4</td>
</tr>
<tr>
<td>Granite Wash</td>
<td>1,3,4</td>
<td>2,7</td>
</tr>
<tr>
<td>Fox Hills</td>
<td>2,7</td>
<td>1,3,4</td>
</tr>
<tr>
<td>Woodbine</td>
<td>1,3,4,6,7</td>
<td>2,8</td>
</tr>
<tr>
<td>Morrison</td>
<td>1,3,4,5,7</td>
<td>2</td>
</tr>
<tr>
<td>Lyons</td>
<td>8</td>
<td>1,2,3,4</td>
</tr>
</tbody>
</table>

Key:

1 = Depth, 2 = Permeability, 3 = Thickness, 4 = Net Sand Thickness, 5 = Temperature, 6 = Pressure, 7 = Salinity, 8 = Porosity
We attempt to determine the degree of error from reconstruction by comparing the supply function and spatial distribution of results when reconstructing properties as opposed to using the interpolated data in the Frio. We are unable to compare interpolated data for temperature, as temperature is reconstructed, but we test a “hot” thermal gradient compared to our average thermal gradient.

Reconstruction of the temperature, pressure, and salinity properties underestimates storage, by as much as 35%, although individually only pressure reconstruction has an error greater than 4% (approximately 16%). Spatially, the quantity and storage can be off by quite a bit (a factor of two, in some cases). In the Frio, these errors are greatest along bands perpendicular to the dip of the formation. To explain this, we hypothesize that the sample data for the Frio may have been taken within a relatively narrow average depth range. Thus there were errors on the shallow end of the Frio’s dip and at the deep end, but not in the middle, and they roughly balanced out overall; the sign of the errors correlates with what we would expect if this were the case. For formations with little variation in depth, we expect reconstruction to produce small errors, but even for heavily dipping formations, we expect reasonable accuracy when reconstructing parameters if the sampled data is near the average depth of the formation. We note, however, that it is unclear which method is more accurate, as the sample points generally do not contain depth information and thus might be off by a considerable amount for thick formations (indicating that better data would improve the quality of results). This rough form of accuracy assessment demonstrates that the analysis probably does not have a high accuracy for any given grid cell, but will be more reliable for larger sample areas.
**B2 Injection Rate**

Injection rate is constrained by the fracturing pressure (Eccles et al. 2009) calculated from the physical properties of sandstone and the pore pressure (Suppe 1985) where the state of effective stress

\[
\sigma_n = \left(\frac{\sigma_1 + \sigma_3 - P_f}{2}\right) + \left(\frac{\sigma_1 - (\sigma_3 - P_f)}{2}\right) \cos(2\theta)
\]  
[B1]

\[
\sigma_T = \left(\frac{\sigma_1 - (\sigma_3 - P_f)}{2}\right) \sin(2\theta)
\]  
[B2]

reaches the failure criterion

\[
\sigma_T = \tau_s + \sigma_n \mu .
\]  
[B3]

These equations are explained in detail in Eccles et al (Eccles et al. 2009). We restrict the downhole bore pressure to 90% of this calculated maximum (Nordbotten et al. 2005) and calculate the injection rate using the equations

\[
X = Kb
\]  
[B4]

\[
S = S_s b
\]  
[B5]

\[
S_s = \rho_w g (\alpha + \phi(z)\beta)
\]  
[B6]

\[
u = \frac{S}{4X} f
\]  
[B7]

\[
Q_{vol} = \frac{-P_f 4\pi X}{g \rho Ei(u)} .
\]  
[B8]

In equation B4, we define \(X\) as the transmissivity of the reservoir, where \(K\) is permeability and \(b\) is layer thickness. In equation B5, \(S\) is the storativity of the reservoir, where \(S_s\) is specific storativity. Specific storativity is calculated with equation B6, in which \(\rho_w\) is the density of the pore water, \(g\) is the acceleration of gravity, \(\alpha\) is the
compressibility of the rock skeleton, $\phi$ is the porosity, and $\beta$ is the compressibility of the pore fluid. Equation B8 is the Theis solution or the well function, in which the volumetric injection rate ($Q_{vol}$) is a function of the injection pressure ($P_f$ 90% of the fracture pressure calculated from Equations B1, B2, and B3), $\pi$ is pi, $\rho$ is the density of the injection fluid, and $Ei(u)$ is the exponential integral of equation B7, where $S$ is storativity, $X$ is transmissivity, and $f$ is a scaling factor. This injection equation is the solution to the radial integration of Darcy’s law (Freeze & Cherry 1979), in the manner also used by Middleton and Bielicki (Middleton & Bielicki 2009), in a method published and explained in more detail in Eccles et al (Eccles et al. 2009). We use the density function for CO$_2$ to calculate a mass flow rate from this volumetric rate. If this exceeds the design maximum of the Sleipner injector well (approximately 3500 tonnes/day (Eccles et al. 2009)), it is restricted to that value.

**B3 Storage Cost**

The cost of an injection well (as a function of depth) amortized to a yearly capital cost divided by this maximum injection rate is the cost per tonne of storage (Eccles et al. 2009).

**B3.1 Additional Cost Scenarios**

The cost figures reported for injection only are very low, as they do not include the majority of site infrastructure or other expenses. For this reason, the capital cost framework from Eccles et al was extended to include other potential costs. As the basis for this cost, we use an EPA technical support document detailing a variety of potential costs on a per-unit basis (Environmental Protection Agency (EPA) 2008). The information in this document comes from several public sources and the majority of the contents thereof can be verified. Of principle concern were the addition of site infrastructure such as centralized equipment, site evaluation and monitoring (i.e. seismic
surveys), distribution pipelines within a site, and various remediation and lifecycle costs associated with a potential sequestration project.

Our original model includes drilling cost data and injection equipment from the Joint Association Survey on Drilling Costs (for public access, summarized in comparison to geothermal costs (Augustine et al. 2006)) and injector equipment (EIA 2007), which were also sources for the EPA document (Environmental Protection Agency (EPA) 2008); we use our original figures for these costs and expand on them with the EIA estimates as summarized by the EPA verified with the original figures. Other costs, such as the cost of distribution pipelines, was also verified in this manner and by comparison with transport models such as that of Parker (Parker 2004) and McCoy and Rubin (McCoy & Rubin 2008a), although there is a degree of uncertainty for the cost of small-diameter pipelines in these models. Of the costs detailed in the EPA document, the most difficult to evaluate was the seismic survey costs, which unfortunately can be a major component of total costs. To the extent possible, these costs were compared with previous site evaluation figures (e.g. Bock (Bock 2002)), although the nature of the reported costs makes these comparisons difficult. For the most part, however, the estimates seemed sound, reflecting use of consulting firms and industry estimates, including those reported to the U.S. government, in other cost models (Middleton & Bielicki 2009).

We integrate several of these costs into the geospatial framework where necessary as described in the text. The costs can be divided into categories based on their unit basis, including fixed site costs, costs per injection well, costs per injection well per unit of depth, costs per unit area of reservoir, and costs per element of infrastructure (such as a monitoring control center). Table 6 includes a description of the various scenarios for coefficient values evaluated in our analysis. Our scenario groups were
meant to explore several options for the scale of the injection site, the amount of distribution pipeline necessary, and the monitoring/shutdown equipment necessary. A geosequestration site could handle a wide variety of annual storage requirements, introducing the possibility of economies of scale for large, centralized sites. We also considered that distribution pipelines would be required from a central receiving station, exploring in our second scenario group different lengths of this distribution network, as the configuration of a geosequestration site on the ground at scale is currently not known. The legal and regulatory framework for monitoring is likewise not known, so our third scenario group explores monitoring infrastructure variations.

Table 7: Geosequestration Site Cost Scenario List and Descriptions

<table>
<thead>
<tr>
<th>Scenario Number</th>
<th>Annual Total Injection Rate</th>
<th>Pipeline</th>
<th>Other</th>
<th>Annualized Capital Costs (not including drilling/injection; amortization factor from Eccles et al.)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mln tonne/year</td>
<td>km 6 in. pipe</td>
<td>Per Site</td>
<td>Per km2</td>
</tr>
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<td>3.65</td>
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<td>$10,877</td>
</tr>
<tr>
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<td>$10,877</td>
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<tr>
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<td>10</td>
<td>0</td>
<td>no shutdown cost</td>
<td>$113,549</td>
</tr>
<tr>
<td>1c</td>
<td>25</td>
<td>0</td>
<td>$117,894</td>
<td>$10,877</td>
</tr>
<tr>
<td>2b</td>
<td>10</td>
<td>1</td>
<td>$117,894</td>
<td>$10,877</td>
</tr>
<tr>
<td>2c</td>
<td>10</td>
<td>5</td>
<td>$117,894</td>
<td>$10,877</td>
</tr>
<tr>
<td>2d</td>
<td>10</td>
<td>10</td>
<td>$117,894</td>
<td>$10,877</td>
</tr>
<tr>
<td>3b</td>
<td>10</td>
<td>0</td>
<td>2 mon. wells</td>
<td>$143,794</td>
</tr>
<tr>
<td>3c</td>
<td>10</td>
<td>0</td>
<td>6 mon. wells, 2 stations, 2 old wells, 2 periodic</td>
<td>$295,964</td>
</tr>
</tbody>
</table>
Although the scale of the project did not appear to have a large effect on the per-tonne cost of geosequestration, the distribution and monitoring did, so we used a conservative combination of the scenario costs to estimate total cost. The value reported in the text reflects this combination of coefficients for the equations described in the text.

The cost values in the original injection-only Eccles et al. model were on a 2005 USD basis; these have been recalculated on a 2007 USD basis to match the EPA document using PPI information (See Table 7); thus far these PPI values match well with 2010 preliminary data and it is not unreasonable to consider the cost data on a current USD basis (Bureau of Labor Statistics (BLS) 2010). For the cost of drilling and the associated equations and coefficients, see Eccles et al (Eccles et al. 2009).

### Table 8: Producer Price Index for Cost Basis Adjustment (Source: Bureau of Labor Statistics)

<table>
<thead>
<tr>
<th>Year</th>
<th>PPI (O&amp;G Extraction)</th>
<th>Notes</th>
</tr>
</thead>
<tbody>
<tr>
<td>2005</td>
<td>262</td>
<td>Original Eccles et al</td>
</tr>
<tr>
<td>2006</td>
<td>252.5</td>
<td></td>
</tr>
<tr>
<td>2007</td>
<td>267.1</td>
<td>EPA cost document</td>
</tr>
<tr>
<td>2008</td>
<td>347.5</td>
<td></td>
</tr>
<tr>
<td>2009</td>
<td>187.3</td>
<td></td>
</tr>
<tr>
<td>2010</td>
<td>241.2</td>
<td>(Preliminary)</td>
</tr>
</tbody>
</table>
References


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