



The Importance of Modeling Carbon Dioxide Transportation and Geologic Storage in Energy System Planning Tools

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Energy system planning tools suggest that the cost and feasibility of climate-stabilizing energy transitions are sensitive to the cost of CO₂ capture and storage processes (CCS), but the representation of CO₂ transportation and geologic storage in these tools is often simple or non-existent. We develop the capability of producing dynamic-reservoir-simulation-based geologic CO₂ storage supply curves with the Sequestration of CO₂ Tool (SCO₂T) and use it with the ReEDS electric sector planning model to investigate the effects of CO₂ transportation and geologic storage representation on energy system planning tool results. We use a locational case study of the Electric Reliability Council of Texas (ERCOT) region. Our results suggest that the cost of geologic CO₂ storage may be as low as \$3/tCO₂ and that site-level assumptions may affect this cost by several dollars per tonne. At the grid level, the cost of geologic CO₂ storage has generally smaller effects compared to other assumptions (e.g., natural gas price), but small variations in this cost can change results (e.g., capacity deployment decisions) when policy renders CCS marginally competitive. The cost of CO₂ transportation generally affects the location of geologic CO₂ storage investment more than the quantity of CO₂ captured or the location of electricity generation investment. We conclude with a few recommendations for future energy system researchers when modeling CCS. For example, assuming a cost for geologic CO₂ storage (e.g., \$5/tCO₂) may be less consequential compared to assuming free storage by excluding it from the model.

Keywords: energy system planning, ReEDS, SCO2T, CCS, supply curve, geologic CO2 storage

ACRONYMS

All acronyms used in this paper are defined in **Table 1**.

INTRODUCTION

Motivation, Literature Review, and Research Gaps

Greenhouse gas (GHG) emissions, principally carbon dioxide (CO₂), drive climate change and thus pose substantial risk to human health and economic growth (Intergovernmental Panel on Climate

TABLE 1 | All acronyms defined.

Acronym	Non-abbreviated form
BECCS	Bioenergy power plants with CO ₂ Capture
CCS	CO ₂ Capture and Storage
CEM	Capacity Expansion Model
EPA	Environmental Protection Agency
ERCOT	Electric Reliability Council of Texas
GAMS	General Algebraic Modeling System
GCAM	Global Change Analysis Model
GHG	Greenhouse Gas
IAM	Integrated Assessment Model
MARKAL	MARKet ALlocation Model
NEMS-CTS	National Energy Modeling System—CO ₂ Capture, Transport, and Storage Model
NREL	National Renewable Energy Laboratory
ReEDS	Regional Energy Deployment System Model
SCO ₂ T	Sequestration of CO ₂ Tool
SI	Supplemental Information
US-REGEN	US Regional Economy, Greenhouse Gas, and Energy Model

Change, 2018). GHGs are primarily emitted from human activities that burn fossil fuels for energy. For example, the energy system—electricity, transportation, heat—collectively emitted ~90% of all GHG emissions in the United States in 2018 (Environmental Protection Agency, 2020). As a result, addressing climate change will require transitioning from the current energy system to one that is comprised of technologies that emit substantially fewer GHGs (Intergovernmental Panel on Climate Change, 2014; Rogelj et al., 2018).

Energy system planning tools are often used to gain insight into prospective energy transitions. For example, Integrated Assessment Models (IAMs) are increasingly being used as energy planning tools given their ability to link climate and energy systems together (Intergovernmental Panel on Climate Change, 2014; Rogelj et al., 2018; Vinca et al., 2018). Additionally, electricity sector Capacity Expansion Models (CEMs) are often used to investigate pathways to decarbonizing electricity specifically, because they can provide more targeted guidance on electricity infrastructure investment decisions. For example, CEMs can be used to determine which technologies should be deployed to supply electricity demand at least cost under a grid-wide CO₂ emission limit or a CO₂ price that increases the cost of technologies that emit CO₂ to the atmosphere (Wise et al., 2007; Frew et al., 2016; MacDonald et al., 2016; Mileva et al., 2016; Pleßmann and Blechinger, 2017; Koltsaklis and Dagoumas, 2018; Sepulveda et al., 2018; Dagoumas and Koltsaklis, 2019; Bistline and Blanford, 2020; Jayadev et al., 2020).

Results from these tools generally suggest there is uncertainty on the extent to which any single technology will be deployed throughout an energy transition given the inherent uncertainties about the future. For example, the deployment of one technology may be affected by the availability and cost of another (Fais et al., 2016). Despite this uncertainty and complexity, results from both IAMs and CEMs suggest that the cost and feasibility of decarbonization transitions are sensitive to the cost and availability of CO₂ capture and storage (CCS) processes (Krey et al., 2014; Kriegler et al., 2014; Yang et al., 2015; Dessens et al., 2016; Sepulveda et al., 2018; Gambhir et al., 2019; Bistline and

Blanford, 2020; Jayadev et al., 2020; Baik et al., 2022). In CCS processes, CO₂ that would otherwise be emitted to the atmosphere is instead captured and compressed, possibly transported, and then injected into the subsurface for permanent storage in deep geologic formations that are naturally porous and permeable (Intergovernmental Panel on Climate Change, 2005). Some studies suggest that climate-stabilizing energy transitions will require injecting up to ~1,200 GtCO₂ globally by 2,100 (Rogelj et al., 2018). And in the United States specifically, the Princeton Net Zero America study demonstrates that at a minimum, 0.9 GtCO₂/yr of CO₂ injection is required to decarbonize by 2050, which is 1.3 times larger than the country's oil production on a volume equivalent basis (Larson et al., 2020; Jenkins et al., 2021).

While important, robustly representing CCS in energy system planning tools is challenging. For one, estimating the cost and capacity of geologic CO₂ storage over the geographical scope of energy systems (e.g., state, continent, globe) is difficult. The subsurface properties that define the geology at any given CO₂ storage site influence its capacity and cost but are always uncertain. These properties also vary geospatially, which means the capacity and cost of geologic CO₂ storage can vary substantially by location. Moreover, the capacity and cost of geologic CO₂ storage can also vary due to site-level factors that can be independent of geology. For example, the diameter of the well casing may constrain the maximum CO₂ injection rate, thus the CO₂ storage capacity, more than geology (Middleton et al., 2020b). But the cost and capacity implications of these site-level factors are understudied, and even though there are no substantial technical challenges to CCS deployment (Akerboom et al., 2021), there are very few geologic CO₂ storage sites in existence for which to base site-level assumptions.

Additionally, representing CCS in energy system planning tools also requires assumptions about CO₂ transportation because it is possible to transport captured CO₂ long distances, via pipeline for example, before subsurface injection. The geologic CO₂ storage formations below any given power plant, if any exist, may or may not be the least-cost location to

TABLE 2 | Representation of CO₂ Transportation and Geologic Storage in Integrated Assessment Model (IAM) and Electric Sector Capacity Expansion Model (CEM) Energy Planning Tools. It is possible to modify any CEM to include CO₂ transportation and geologic storage representation, which has been done, for example with SWITCH (Sanchez et al., 2015), but this table lists the default representation. Costs were converted to 2017 dollars following the method published in prior work (Koelbl et al., 2014).

Model name	Type	Include CO ₂ transportation and geologic storage?	Cost of CO ₂ transportation and geologic storage* [2017\$/tCO ₂]	Supply curves used to define cost-capacity relationships?
MARKAL + EPAUS9r2014 database Lenox et al. (2013); Victor et al. (2018)	Includes a CEM component	Yes	2.63–26.8	No
NEMS-CTS Zelek et al. (2012)	Includes a CEM component	Yes	9.54 ^a –21.04 ^a	No
US-REGEN Electric Power Research Institute (2020)	Includes a CEM component	Yes	1.69–9.29	No
OseMOSYS Howells et al. (2011)	CEM	No	0.00	N/A
GenX Jenkins and Sepulveda (2017); Sepulveda et al. (2018)	CEM	No	0.00	N/A
ReEDS 2.0 National Renewable Energy Laboratory (2019a)	CEM	No	0.00	N/A
SWITCH 2.0 Johnston et al. (2019)	CEM	No	0.00	N/A
WIS:dom-P Vibrant Clean Energy (2020)	CEM	No	0.00	N/A
Many IAMs Koelbl et al. (2014)	IAM	Yes	0.14 ^b –418.98	Sometimes

^aMost recent estimates published from the tools which are used in National Energy Modeling System (NEMS) (National Energy Technology Laboratory, 2019).

^bIncreases to \$6.98/tCO₂ if Global Change Analysis Model (GCAM) is excluded.

*It is possible that these ranges may overstate differences between the tools (e.g., if the majority of CO₂ storage is available at similar costs). We provide cost comparisons independent of the quantities of storage available because the variety of assumptions used, and sometimes opaque documentation, makes it difficult to compare cost-capacity relationships more directly.

store the captured CO₂ when considering the geospatial variability of CO₂ storage capacities and costs, the cost of CO₂ transportation, and other costs like electricity transmission infrastructure (Hannon and Esposito, 2015). Further, determining a least-cost CO₂ transportation network is non-trivial, even if all the CO₂ point sources and potential sinks are identified (Middleton and Bielicki, 2009; Wu et al., 2015; Middleton et al., 2020c). Capturing the systems-level ramifications of CO₂ transportation endogenously within an energy system planning tool is even more difficult because the power plants equipped with CO₂ capture (i.e., the CO₂ point sources) have not been identified, and are instead a possible option that the model may, or may not, deploy.

Due to these challenges, the representation of CCS in energy system planning tools varies (Table 2). For example, all “out of the box” CEMs by default include power plants equipped with CO₂ capture as a technology option, but most do not represent CO₂ transportation or geologic storage in any way. This exclusion is typically justified by assuming that 1) the cost of CO₂ capture drives investment decisions because it accounts for the largest share of CCS-related costs and/or 2) the capacity and cost of geologic CO₂ storage is driven by geologic factors that are outside the domain of the model. Regardless of the justification, this exclusion means the majority of CEMs implicitly assume that CO₂ transportation and geologic storage is free, and therefore, results from these CEMs misrepresent the cost of deploying and operating CCS.

The few CEMs that include CO₂ transportation and geologic storage assume a wide range of costs. For example, the cost

estimates in the MARKET and ALLOCATION model (MARKAL) range over an order of magnitude, and the cost ranges in National Energy Modeling System—CO₂ Capture, Transport, and Storage model (NEMS-CTS) and the US Regional Economy, Greenhouse Gas, and Energy model (US-REGEN) do not overlap (Table 2). These assumed costs are different from one another because different assumptions are made to address the previously discussed complexity and uncertainty around CCS representation. Some of these assumptions include: using cost and capacity relationships that were estimated independent from one another (Lenox et al., 2013; Victor et al., 2018); using cost estimates made for specific locations to represent the cost of CO₂ transportation and geologic storage over entire regions (Zelek et al., 2012; National Energy Technology Laboratory, 2019); or assuming a CO₂ pipeline of constant length and diameter for a given power plant type to estimate CO₂ transportation cost (Electric Power Research Institute, 2020). Further, these are single-cost relationships for a given area (e.g., state, region) even though supply curves are the typical way cost-capacity relationships are defined for a given resource in energy system planning tools. In contrast, some IAMs do use supply curves to represent cost-capacity relationships, but the range of costs is even greater than in CEMs, with some IAMs assuming upper limits above \$400/tCO₂.

Contributions and Scope of This Paper

In this study, we address these knowledge gaps by 1) presenting a new approach for generating dynamic-simulation-based supply curves for geologic CO₂ storage and 2) using these curves to

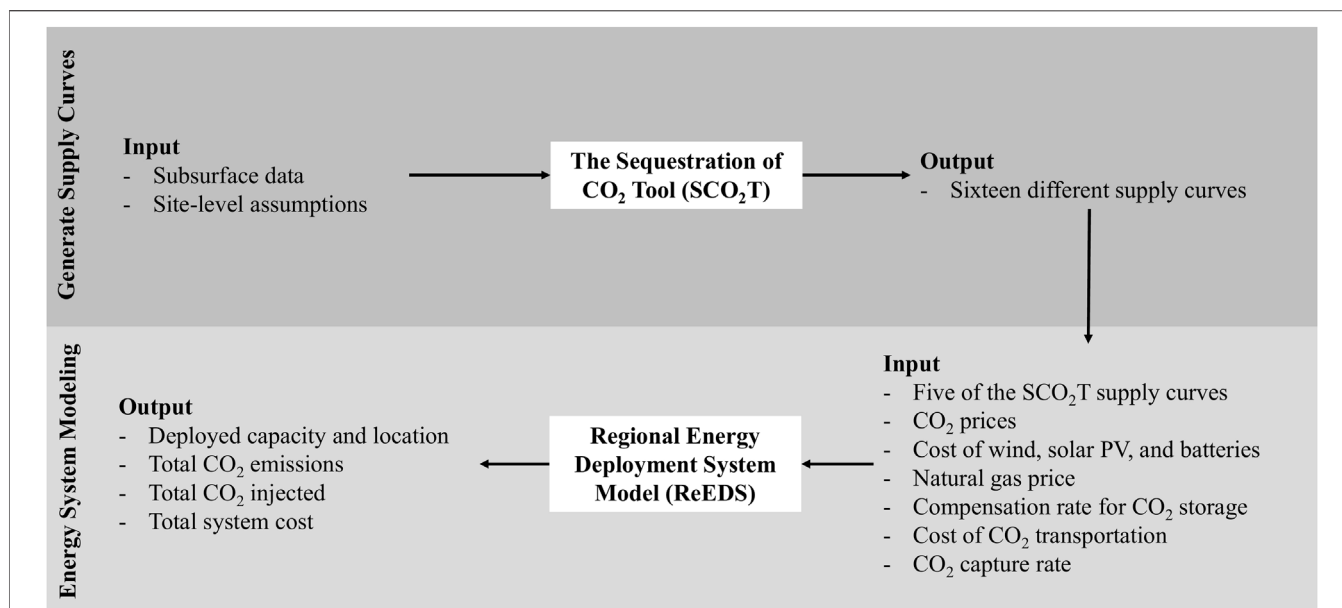


FIGURE 1 | Framework for quantifying the effect that CO₂ transportation and geologic storage assumptions could have on energy system planning tool results.

investigate the grid-level ramifications, such as deployment decisions and CO₂ emissions, of CO₂ transportation and geologic storage assumptions. Our investigation is novel in multiple ways. For one, we present the first dynamic-simulation-based supply curves for geologic CO₂ storage and the first investigation of how those supply curves may change based on site-level factors (e.g., number of monitoring wells per injection well). Prior work, for example Vikara et al. (2017), developed supply curves for geologic CO₂ storage using volumetric approaches to estimate CO₂ storage capacity. Volumetric-based assessments use algebraic equations to estimate the capacity of a potential CO₂ storage site (i.e., multiply the pore volume of the rock by the density of CO₂ and an assumed “efficiency” coefficient). In contrast, our method is based on an entirely different and novel way of estimating the capacity of CO₂ storage that relies on dynamic reservoir simulation and machine learning algorithms. As a result, our supply curves are “dynamic-simulation-based” and do not rely on the assumptions required for volumetric methods in any way. Further, prior work has studied how geology may impact the cost and capacity of CO₂ storage (Anderson, 2017; Vikara et al., 2017; Middleton et al., 2020b), but how site-level factors may affect the cost and capacity of geologic CO₂ storage has, to our knowledge, not been previously investigated.

Additionally, we are the first to quantify the effect that CO₂ transportation and geologic storage assumptions could have on a variety of energy system planning tool results (e.g., CO₂ emissions, total system cost). We do this to gain a better understanding of what situations likely require a more robust representation of CCS compared to the current status-quo. There are many different reasons to use an energy system planning tool, and each application has many assumptions beyond those related to CCS that affect the results (e.g., natural gas price). Further, CO₂

transportation and geologic storage are just two components of the CCS process, and in turn, CCS is just one of many options that a given tool may, or may not, deploy to supply energy. As a result, it is possible that current assumptions regarding CCS are sufficient for some applications, but it is also possible that there are situations in which more robust representations are warranted. As a result of this purpose and the dearth of studies in this area, we draw conclusions with the intent of guiding future energy system modelers when considering how to represent CCS in their tools.

METHODS

As shown in **Figure 1**, our methodology consists of modifying two previously published tools and performing scenario analysis with each of them: the Sequestration of CO₂ Tool (SCO₂T) (Middleton et al., 2020a; Middleton et al., 2020b) and the 2019 open-access version of the Regional Energy Deployment System model (ReEDS) (National Renewable Energy Laboratory, 2019a). In this section, we provide a brief description of our modification and application of these two tools and provide more details in the Supplemental Information (SI). We adjust results from both tools to 2017 dollars because that was the dollar used in our prior work with SCO₂T (Middleton et al., 2020a).

SCO₂T is an Excel-based tool that estimates the capacity and cost of a geologic CO₂ storage site given underlying geologic properties. To do this, SCO₂T uses reduced-order models that replicate full-physics dynamic reservoir simulations (Chen et al., 2020). We modify SCO₂T by 1) adding all site-level costs from the Environmental Protection Agency (EPA) geologic CO₂ storage cost model (Environmental Protection Agency, 2010); 2) adding an Excel MACRO to generate supply curves; and 3) removing

areas from the SCO₂T subsurface dataset that prior work suggests cannot be developed for geothermal power plants or geologic CO₂ storage sites (Young et al., 2019; Hoover et al., 2020). Below we list some assumptions made to apply the EPA cost model for SCO₂T for this study. For example, the EPA provides some cost estimates in the units of \$/site, which required adding inputs for the maximum site size. **Section 1** of the SI contains more information on these modifications.

- In keeping with ReEDS scope that does not include decommissioning cost for power plants, we do not include a post-injection monitoring period or site closure costs in this study.
- We add two ways to constrain the maximum size of a single site within SCO₂T: total injection capacity [MtCO₂/yr] and number of CO₂ injection wells [wells/site]. SCO₂T estimates the CO₂ injection rate for a single well, and then whichever of these two constraints is limiting determines how many sites are financially accounted for within a given SCO₂T run.
- We assume the entire thickness of the formation is drilled for each stratigraphic well and that each core is 9 m long.
- We use a well and pump model from prior work to estimate the power required to inject CO₂ across a range of depths and injection mass flowrates (Adams et al., 2015). We then use this data to regress an equation for pumping power, which is used to estimate the capacity, thus cost, of CO₂ injection pumps. We assume the downhole pressure is 80% of the lithostatic pressure (this is the maximum downhole pressure allowable within SCO₂T to eliminate potential of the formation fracturing from CO₂ injection) to be conservative because this assumption will result in the largest pumping power, thus largest pump cost, estimate.
- In a separate calculation, we use the well and pump model to estimate the electricity required to inject CO₂ across a few scenarios of more realistic downhole overpressures (e.g., only up to 10 MPa of additional pressure above hydrostatic). None of these scenarios resulted in positive pumping power, thus we do not account for a cost of electricity.
- While a single CO₂ plume has the area of a circle, we assume the plume area has the shape of a square when estimating the “Active Monitoring Area” because the total plume size shape at a given site becomes more square-like as more injection wells are drilled (Middleton et al., 2020b).

ReEDS is a widely published CEM of the continental U.S. power system that simulates generation and transmission investment and operating decisions from 2010 to 2050. Out of the different energy system planning tools, we use ReEDS for two primary reasons. First, it has the regional resolution necessary to robustly explore grid-level effects of CCS representation. Other models, such as IAMs, do not easily lend themselves to considering regional and site-specific differences in the cost or capacity of geologic CO₂ storage because they often have coarser spatial resolutions (e.g., continents, globe). Second, ReEDS comes “pre-packaged” with arguably the most thorough and respected sets of CEM input data (e.g., wind energy potential, projected future costs of batteries). As a result, using ReEDS enables us to

execute many scenarios easily, and grounds our conclusions on a robust range of input data. The modifications that we make to ReEDS include adding constraint equations and additions to the objective function to 1) constrain the amount of CO₂ that could be geologically stored; 2) incorporate CO₂ transportation; and 3) account for the cost of CO₂ transportation and geologic CO₂ storage. While it is possible that sequestered CO₂ could leak from the wells with time, prior work suggests this possibility has likely negligible impacts on CCS deployment in the energy system (Deng et al., 2017). As a result, we do not account for CO₂ leakage in this study. Below we list a few of the key assumptions made to implement CO₂ transportation and geologic storage in ReEDS for this study. Section 2 of the SI contains more information on these modifications.

- We use prior work to guide our financing assumptions for geologic CO₂ storage sites (National Energy Technology Laboratory, 2017). For example, we use the 5-year depreciation schedule and 6-year construction time schedule options within ReEDS for geologic CO₂ storage.
- We conservatively require ReEDS to deploy enough geologic CO₂ storage capacity to hold the CO₂ that would be captured over a 30-year power plant lifetime at a 100% capacity factor.
- We follow ReEDS convention and linearly interpolate CO₂ captured in-between model years to estimate the amount of CO₂ captured in gap years (i.e., years in-between ReEDS decision years).

Case Study and Description of Scenarios

We use the Electric Reliability Council of Texas (ERCOT) as a locational case study for several reasons. First, ERCOT is a simpler case study compared to the other options within ReEDS (i.e., Eastern Interconnect, Western Interconnect, or Nationwide), which is appropriate given the purpose of our study and the status-quo of 1) developing regional, dynamic-simulation-based, supply curves for CO₂ storage and 2) CCS representation in energy system planning tools. Second, ERCOT manages approximately 90% of the electric load in Texas with a record peak demand of nearly 75 GW (Electricity Reliability Council of Texas, 2021) and is electrically isolated from the Eastern, Western Interconnections, and the Mexican Power Grid with only a small portion of demand being supplied with imports. As a result, ERCOT is a common electricity system case study, with much prior work using it to provide insights into electricity systems broadly (Denholm and Hand, 2011; Sepulveda et al., 2018; Ogland-Hand et al., 2019). Finally, much of the existing geologic CO₂ storage infrastructure in the United States is in Texas for enhanced oil recovery.

We execute our study in two parts. First, we run SCO₂T across ERCOT (13,601 10 × 10 km grid cells) for sixteen different scenarios of site-level assumptions to generate sixteen separate supply curves (i.e., each supply curve is generated from 13,601 SCO₂T runs). These supply curves can be used to understand the effects that site-level assumptions may have on ERCOT-wide costs and capacities of geologic CO₂ storage. The supply curve

TABLE 3 | Description of Parameter Space Used in Electricity System Analysis. We execute ReEDS for every combination of parameters listed when the CO₂ capture rate is 90% (default capture rate in ReEDS), but only for a portion of the geologic CO₂ storage cost-capacity relationship when the CO₂ capture rate is 85% or 95%. The 90% default capture rate is common in many studies because it is a historical benchmark based on economic studies of CO₂ capture (International Energy Agency Greenhouse Gas, 2019). Unless specified, we use ReEDS default inputs for the Mid case in the 2019 NREL Standard Scenarios report (National Renewable Energy Laboratory, 2019b).

Input parameter	Description
Geologic CO ₂ Storage Cost-Capacity Relationships (Section 4.1.1 of the SI)	We use five of the sixteen SCO ₂ T supply curves and three other scenarios of unlimited storage with an annualized cost of \$0/tCO ₂ , \$5/tCO ₂ , and \$20/tCO ₂ (all in 2017 dollars). Of the sixteen supply curves created, we used the two with the highest cost, the two with the lowest cost, and one with costs that were intermediate to the others
CO ₂ Transportation Cost (Section 4.1.2 of the SI)	We assume annualized costs of CO ₂ transportation of \$0/tCO ₂ , \$1/tCO ₂ , and \$2/tCO ₂ (all in 2004 dollars), which are based off prior work that suggests the cost is approximately \$2/tCO ₂ National Energy Technology Laboratory (2019)
Natural gas prices (Section 4.1.3 of the SI)	We use the three scenarios (low, medium, high) that are available within ReEDS.
Wind turbines, solar photovoltaic (PV), and battery costs (Section 4.1.4 of the SI)	We use the three scenarios (low, medium, constant) that are available within ReEDS.
CO ₂ prices that increase the cost of power plants that emit CO ₂ (Section 4.1.5 of the SI)	We use scenarios of 1) no CO ₂ price, 2) low CO ₂ prices (\$8/tCO ₂ in 2020 to \$35/tCO ₂ in 2050, in 2004 dollars), and 3) high CO ₂ prices (\$41/tCO ₂ in 2020 to \$164/tCO ₂ in 2050, in 2004 dollars). The non-zero scenarios are the price trajectories that prior work from the IPCC suggests are required to limit the atmospheric concentration of CO ₂ to between 650 and 720 ppm or between 430 and 480 ppm, respectively Intergovernmental Panel on Climate Change (2014)
Compensation rates for geologic CO ₂ storage that decrease the cost of CO ₂ injection (Section 4.1.6 of the SI)	We use scenarios of \$0/tCO ₂ and \$65/tCO ₂ (in 2017 dollars). Modeling a policy that decreases the cost of CCS by providing compensation for geologically storing CO ₂ is motivated by the 45Q tax incentive in the United States, but these scenarios are not intended to represent 45Q

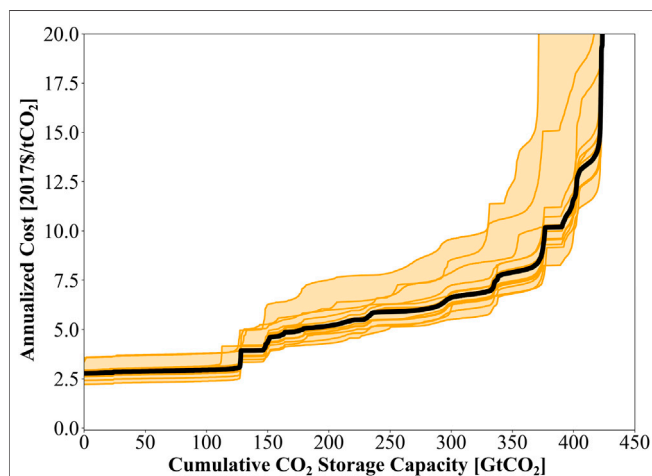


FIGURE 2 | Supply Curve Variability Across All Sixteen SCO₂T Scenarios. The black curve is the baseline SCO₂T scenario, and the orange curves and area cover the range of how costs and capacities may change based on different site level assumptions. See **Supplementary Figure S3** in the SI for SCO₂T scenario labels.

scenarios are further described in **Section 3** of the SI. Second, we use five of these supply curves that cover the cost ranges of all sixteen as geologic CO₂ storage scenarios in ReEDS within a larger electricity system analysis framework. Overall, we run

2,592 distinct combinations in ReEDS of different cost, price, CO₂ capture rate, and policy scenario assumptions (**Table 3**) because there are many required inputs that affect results, and our goal is to provide future researchers with a better understanding of what situations likely require more robust assumptions around CCS compared to the current simple or non-existent representations.

RESULTS AND DISCUSSION

Geologic CO₂ Storage Supply Curves Produced With SCO₂T

To our knowledge, **Figure 2** shows the first supply curve for geologic CO₂ across an energy system as large as ERCOT that is based on dynamic reservoir simulation results. First, it illustrates that there is a tremendous capacity available for geologic CO₂ storage in ERCOT at low cost. For example, approximately 350 GtCO₂ (30% of the possible 1,200 GtCO₂ global maximum capacity needed (Rogelj et al., 2018)) of geologic CO₂ storage capacity is available in ERCOT at or below \$8/tCO₂, and approximately 100 GtCO₂ of this capacity is available at or below \$3/tCO₂. These costs are lower than most assumed estimates currently used in energy system planning tools (**Table 2**), but align with industry estimates and actual geologic CO₂ storage projects that suggest that the cost of geologic CO₂ storage is likely between \$2/tCO₂ and \$4/tCO₂ (Riestenberg et al., 2017; Holubnyak and Dubois, 2018).

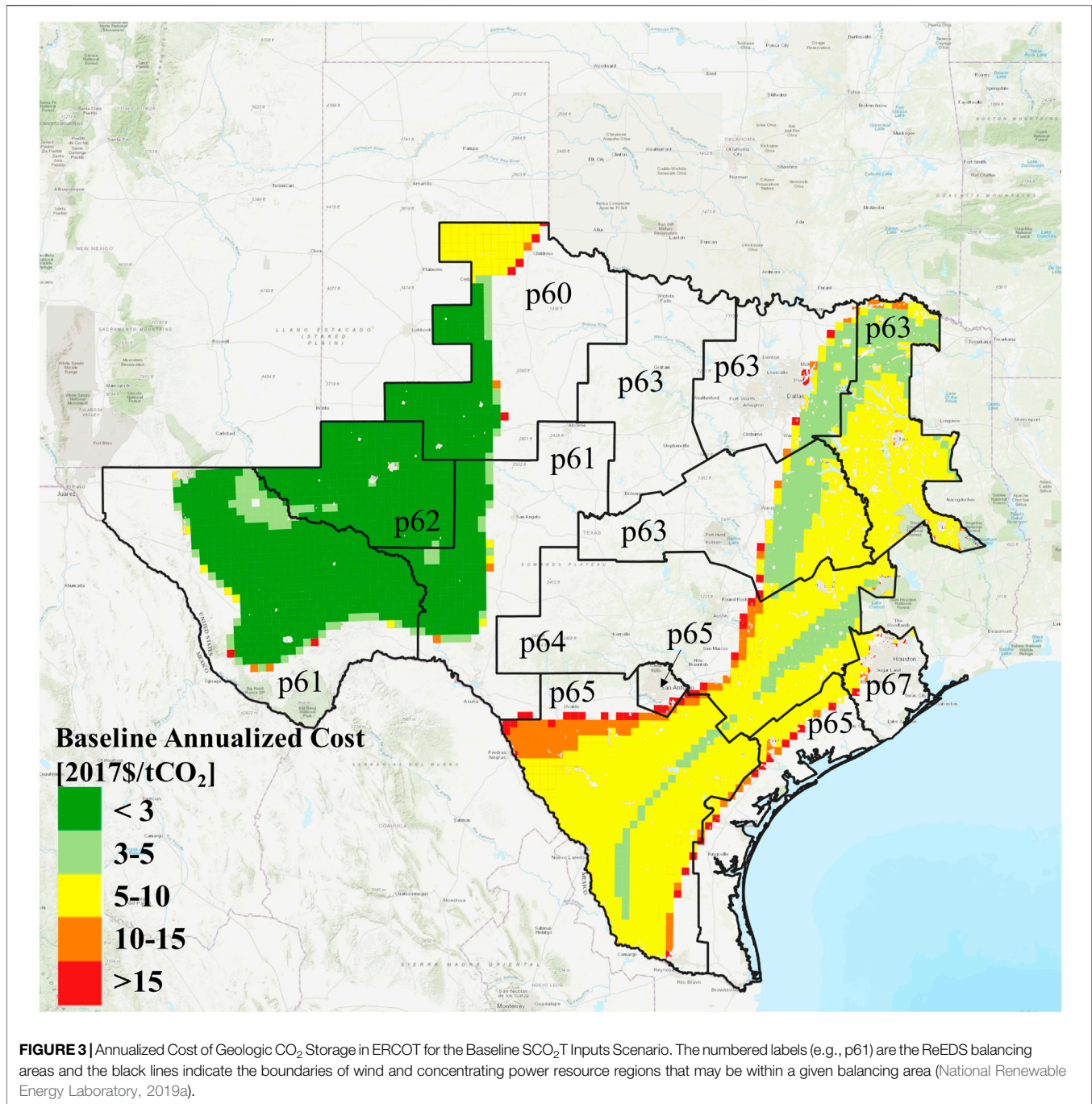
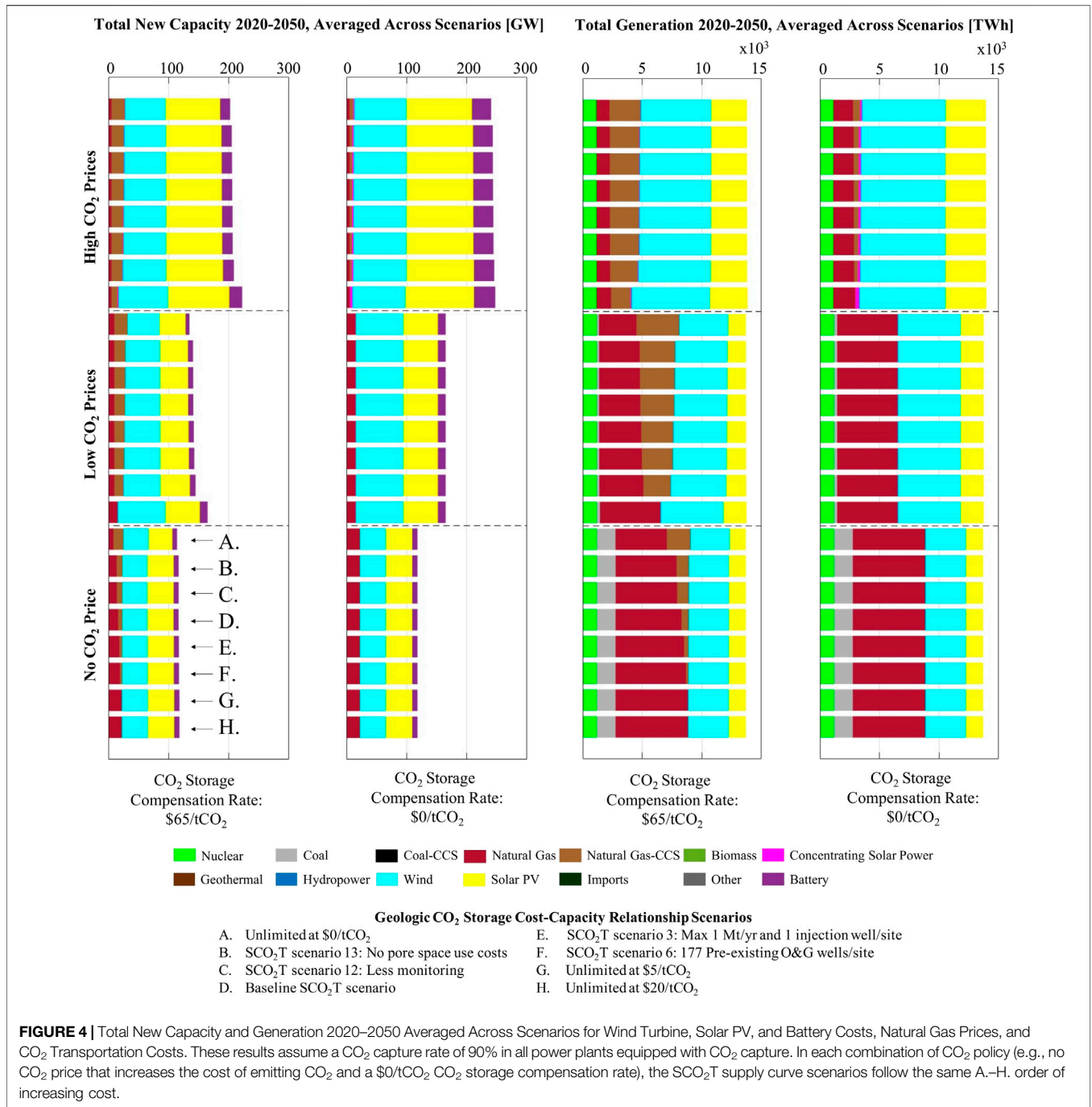


Figure 2 also demonstrates that the site-level assumptions influencing the cost of geologic CO₂ storage can change costs by a few dollars per tCO₂, which is not negligible considering that the costs are only around \$3/tCO₂ for the least expensive 100 GtCO₂ of capacity. Further, when compared against our prior work that demonstrates that reservoir depth, porosity, and thickness can change costs by ~\$2/tCO₂, ~\$4/tCO₂, or ~\$5/tCO₂, respectively (Middleton et al., 2020b), the results in **Figure 2** suggest that site-level factors may influence costs on a similar order of magnitude as geology. Given this level of sensitivity, and because this is the

first study to consider the cost implications of site-level factors over a large area (i.e., ERCOT), we suggest future work continues to investigate how these factors may affect cost. Especially considering that some of these factors (e.g., monitoring costs) are a result of policies that could be changed.

Last, **Figure 2** suggests that the baseline SCO₂T inputs (black line) provide cost estimates that are intermediate to cost estimates from the more extreme SCO₂T input assumption scenarios (orange lines and area). As a result of this and the overall sensitivity of cost to site-level factors, we suggest that future



work use baseline SCO₂T inputs for CO₂ storage supply curves until there are more geologic CO₂ storage projects deployed that can be used to guide site-level assumptions.

Figure 3 shows the geospatial distribution of geologic CO₂ storage costs across ERCOT using the baseline SCO₂T input scenario. There are geologic CO₂ storage resources in every area that electricity supply and demand are matched within ReEDS (i.e., ReEDS balancing areas), but the costs of these resources vary. The least-expensive geologic CO₂ storage resources are in West ERCOT (balancing areas p60, p61, and p62), while the more

expensive resources are in the East (balancing areas p63, p64, p65, and p67). When considered with Figure 2, Figure 3 demonstrates the importance of the higher resolution estimates that SCO₂T enables. For example, the NEMS-CTS model uses an estimated cost of geologic CO₂ storage of \$9/tCO₂ (in 2018 dollars) for the region that includes Texas, which was developed assuming basin geology that is characteristic of East Texas (National Energy Technology Laboratory, 2019). Without the higher resolution SCO₂T cost estimates, it would be difficult to know that this estimate is arguably not representative of costs in Texas.

Grid-Level Effects of CO₂ Transport and Geologic Storage Assumptions

Figure 4 shows the total new capacity deployed and total generation of each technology from 2020 to 2050, averaged across all scenarios of wind turbine, solar PV, and battery costs, natural gas prices, and CO₂ transportation costs for each combination of CO₂ policy and CO₂ storage cost-capacity relationship. The 2020–2050 period was used to make differences across scenarios more apparent because the 2010–2019 deployment and generation is prescribed in ReEDS. We first present **Figure 4** to facilitate a general discussion on the effects that the CO₂ policies and geologic CO₂ storage cost scenarios may have on deployment and dispatch decisions, because CEMs are primarily used to investigate such results. As energy system planning tools can also be used for other purposes, we follow by discussing the sensitivity of other grid-level results to assumptions about geologic CO₂ storage (Section 3.2.1) and CO₂ transportation (Section 3.2.2).

Across all combinations of CO₂ policy and geologic CO₂ storage that we consider, there is more investment in variable renewable energy technologies compared to any other technology. For example, approximately two-thirds or more of all deployment across all CO₂ policy combinations is solar PV and wind turbines. No coal power plants with CO₂ capture are deployed and the deployment of natural-gas power plants with CO₂ capture is highly reliant on CO₂ policies. Natural-gas power plants with CO₂ capture are generally deployed at comparable capacities, if not less, than new natural-gas power plants without CO₂ capture. More general discussion about these general results, including what services power plants with CO₂ capture provide, is included in Section 6.2 of the SI.

The results in **Figure 4** demonstrate that the assumed cost of geologic CO₂ storage has the largest effect on deployment and dispatch decisions in policy scenarios that render CCS marginally competitive compared to other energy technologies. For example, when the CO₂ policy renders natural gas power plants with CO₂ capture less expensive (e.g., geologic CO₂ storage compensation rate of \$65/tCO₂ and high CO₂ prices) or more expensive (e.g., geologic CO₂ storage compensation rate of \$0/tCO₂ and low CO₂ prices) relative to other energy technologies, the average investment and average generation become relatively insensitive to the assumed cost of geologic CO₂ storage. In contrast, when the CO₂ policy renders natural gas power plants with CO₂ capture only marginally competitive on cost (e.g., geologic CO₂ storage compensation rate of \$65/tCO₂ and no CO₂ price), small increases to the assumed cost of geologic CO₂ storage (e.g., <\$1/tCO₂) can result in large changes to investment or generation because other energy technologies (i.e., natural gas without CO₂ capture in this policy combination) become marginally less costly in comparison. This sensitivity of average investment in, and average generation of, natural-gas power plants with CO₂ capture to CO₂ policy occurs because the CO₂ policy combination determines when natural gas power plants with CO₂ capture compete closely with other energy technologies.

Sensitivity to Geologic CO₂ Storage Cost

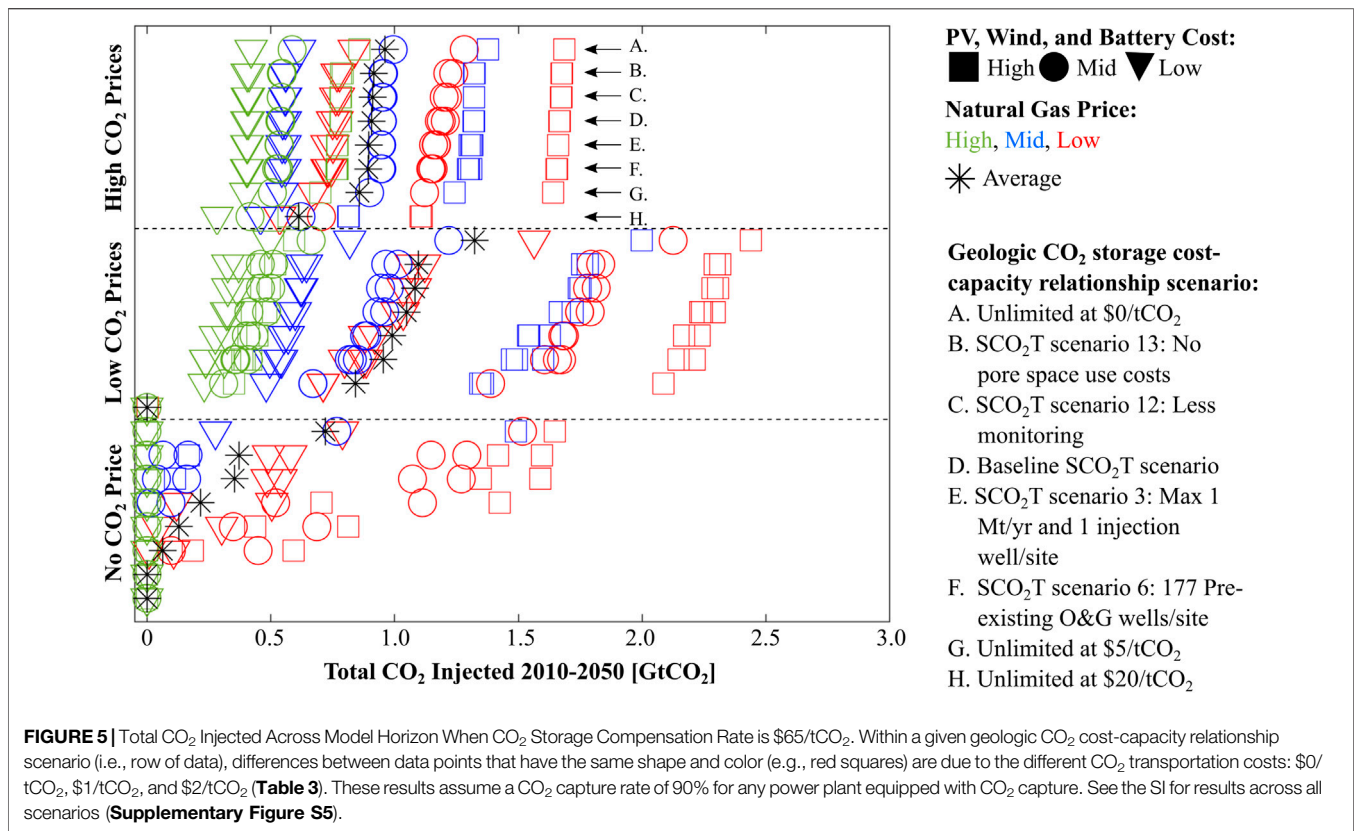
Figure 5 shows the variability of total CO₂ injected across every combination of CO₂ prices, wind, solar PV, and battery costs, natural gas prices, CO₂ transportation costs, cost of geologic CO₂ storage, and CO₂ capture rate that we considered when the compensation rate for geologic CO₂ storage is \$65/CO₂. We focus on this subset of scenarios because there is comparatively minor investment in, and dispatch of, CCS capacity in the other scenarios (**Figure 4**). The SI includes similar figures for different grid-level outcomes: total investment in natural gas power plants with CO₂ capture (**Supplementary Figure S6**); total investment in wind and solar energy technologies (**Supplementary Figure S7**); total CO₂ emissions (**Supplementary Figure S8**); total system cost (**Supplementary Figure S9**); and 2050 average CO₂ emission rate (**Supplementary Figure S10**).

First, **Figure 5** suggests that for our scenario assumptions, there are orders of magnitude more capacity for geologic CO₂ storage in ERCOT than needed by the electricity system. For example, a maximum of about 2.8 GtCO₂ are cumulatively injected by 2050, which is approximately 2.4% of the total geologic CO₂ storage capacity available in ERCOT at or below \$5/tCO₂ (**Figure 2**).

Second, **Figure 5** and the accompanying figures in the SI can be used to qualitatively compare the effects that the ranges of assumed inputs have on grid-level impacts. Overall, these figures suggest that the grid-level results are generally more sensitive to input assumptions (e.g., CO₂ policy, the price of natural gas) than to the cost of geologic CO₂ storage. For example, when the compensation rate for storing CO₂ is \$65/tCO₂ in the low CO₂ prices scenario, the amount of CO₂ injected during any given geologic CO₂ storage cost scenario varies between approximately 0.5 GtCO₂ and 2.5 GtCO₂, depending on the price of natural gas and the cost of solar PV, wind, and batteries. Similarly, changes in the assumed power plant CO₂ capture rate generally result in smaller changes to other grid-level results compared to the CO₂ policy scenario; the price of natural gas; or the cost of solar PV, wind, and batteries—all else constant (**Figure 5**; **Supplementary Figure S4**; **Supplementary Figure S5**; **Supplementary Figure S6**; **Supplementary Figure S7**; **Supplementary Figure S8**; **Supplementary Figure S9**).

Third, while other assumed inputs (e.g., the price of natural gas) drive any given grid-level result more than the cost of CO₂ storage, the cost of geologic CO₂ storage was the only input that could eliminate CO₂ injection in some policy combinations (e.g., when the geologic CO₂ storage compensation rate was \$65/tCO₂ in the low CO₂ prices scenario). This finding is important to highlight because, like the other cost and price scenarios, all geologic CO₂ storage cost scenarios used in this study are within the cost ranges that are currently assumed in energy planning tools (**Table 2**). As a result, it is possible that prior studies underestimated the deployment of power plants with CO₂ capture by overestimating the cost of geologic CO₂ storage, even in scenarios in which these power plants were more than marginally competitive on cost with other energy technologies.

Table 4 provides statistics that quantify the variability in grid-level results across geologic CO₂ storage cost scenarios when the



CO₂ compensation rate was \$65/tCO₂ and no CO₂ price. We use results from this specific policy combination because it is the one in which the average total investment and average total generation are most sensitive to the assumed cost of geologic CO₂ storage (Figure 4).

Table 4 shows that in policy scenarios that render CCS marginally competitive, it is still possible that assumptions around the cost of geologic CO₂ storage may have a small influence on results, depending on the metrics of interest. For example, outside of the total investment in natural gas power plants with CO₂ capture and total amount of CO₂ injected, the grid-level result that is most sensitive to the assumed cost of CO₂ storage is the 2050 average CO₂ emission rate. This occurs because natural-gas power plants without CO₂ capture are deployed instead of natural-gas power plants with CO₂ capture as the assumed cost of geologic CO₂ storage increases (Figure 4). In turn, the grid-level result that is least sensitive to the cost of CO₂ storage in this CO₂ policy combination is the total investment in wind and solar energy technologies because as the cost of CO₂ storage increases, the natural gas power plants with CO₂ capture are generally not replaced with investment in wind and solar energy technologies. As a result, depending on the reason why a given energy system planning tool is used, non-robust assumptions around geologic CO₂ storage representation may not substantially influence results.

Table 4 also suggests that it may be less consequential to overestimate the cost of geologic CO₂ storage compared to assuming it is free: the mean and standard deviations between

the \$0/tCO₂ cost scenario and the five SCO₂T supply curve scenarios (third row in each section of Table 4) are generally larger compared to the mean and standard deviations between the \$20/tCO₂ or \$5/tCO₂ cost scenarios and the five SCO₂T supply curve scenarios (first and second rows in each section of Table 4). This result occurs in this CO₂ policy scenario because natural-gas power plants with CO₂ capture are deployed when the cost of geologic CO₂ storage is \$0/tCO₂, but there are some SCO₂T supply curve scenarios that render natural-gas power plants with CO₂ capture non-competitive on cost compared to natural-gas power plants without CO₂ capture (Figure 4). As a consequence, when SCO₂T supply curve scenarios are used, the grid-level results are more similar to when geologic CO₂ storage is assumed to cost \$20/tCO₂ or \$5/tCO₂ than \$0/tCO₂. This finding suggests that if SCO₂T supply curves cannot be used, overestimating the cost of geologic storage (i.e., \$5/tCO₂) may be a more justifiable choice compared to assuming it is free by excluding it from the model.

Lastly, Table 4 also shows the mean and standard deviations between the baseline SCO₂T supply curve cost scenario and the four other SCO₂T supply curve scenarios (fourth row in each section of Table 4) are smaller than the other comparisons (rows). This relationship occurs because the assumed costs of geologic CO₂ storage are closer across this comparison, but these differences are non-zero. As a result, while we suggest future work use the baseline SCO₂T inputs because they are intermediate to the supply curves generated with the more extreme input assumptions (Figure 2), future researchers should be wary that

TABLE 4 | Distribution of Differences Across CO₂ Storage Cost-Capacity Scenarios When CO₂ Storage Compensation Rate is \$65/tCO₂ in the No CO₂ Price Scenario: Mean (Standard Deviation in Parentheses). These results are for a CO₂ capture rate of 90%. All differences are between the same combination of inputs (e.g., natural gas price). The “all SCO₂T scenarios” refers to the five SCO₂T scenarios (labeled B, C, D, E, and F in **Figure 5**) that were used within ReEDS (**Table 3**). The final comparison (row four of each section) is between the baseline SCO₂T scenario (labeled D in **Figure 5**) and the other four SCO₂T scenarios (labeled B, C, E, and F in **Figure 5**). Please see the referenced Figures in the SI to see the distribution results across all scenarios.

Grid-level result	CO ₂ storage cost-capacity relationship scenario comparison	Difference	Percent difference
Natural Gas-CCS Investment [GW] (Supplementary Figure S6)	Unlimited at \$20/tCO ₂ vs. all SCO ₂ T scenarios	6.82 (11.86)	200 (0)
	Unlimited at \$5/tCO ₂ vs. all SCO ₂ T scenarios	6.82 (11.86)	200 (0)
	Unlimited at \$0/tCO ₂ vs. all SCO ₂ T scenarios	9.71 (11.52)	124.29 (73.55)
	Baseline SCO ₂ T vs. other SCO ₂ T scenarios	2.65 (4.28)	75.52 (65.39)
Wind and Solar Energy Technology Investment [GW] (Supplementary Figure S7)	Unlimited at \$20/tCO ₂ vs. all SCO ₂ T scenarios	1.6 (3.08)	2.25 (4.17)
	Unlimited at \$5/tCO ₂ vs. all SCO ₂ T scenarios	1.6 (3.08)	2.25 (4.17)
	Unlimited at \$0/tCO ₂ vs. all SCO ₂ T scenarios	4.36 (5.7)	5.18 (5.63)
	Baseline SCO ₂ T vs. other SCO ₂ T scenarios	0.67 (1.53)	0.98 (1.81)
Total CO ₂ Emissions [GtCO ₂] (Supplementary Figure S8)	Unlimited at \$20/tCO ₂ vs. all SCO ₂ T scenarios	0.18 (0.34)	3.27 (6.28)
	Unlimited at \$5/tCO ₂ vs. all SCO ₂ T scenarios	0.18 (0.34)	3.27 (6.28)
	Unlimited at \$0/tCO ₂ vs. all SCO ₂ T scenarios	0.38 (0.43)	7.19 (7.49)
	Baseline SCO ₂ T vs. other SCO ₂ T scenarios	0.11 (0.18)	2.04 (3.49)
Total System Cost [2017\$B] ^a (Supplementary Figure S9)	Unlimited at \$20/tCO ₂ vs. all SCO ₂ T scenarios	18.47 (33.33)	3.15 (5.61)
	Unlimited at \$5/tCO ₂ vs. all SCO ₂ T scenarios	18.47 (33.33)	3.15 (5.61)
	Unlimited at \$0/tCO ₂ vs. all SCO ₂ T scenarios	24.35 (29.66)	3.88 (4.6)
	Baseline SCO ₂ T vs. other SCO ₂ T scenarios	9.42 (16.03)	1.56 (2.62)
Total CO ₂ Injected [MtCO ₂] (Figure 5)	Unlimited at \$20/tCO ₂ vs. all SCO ₂ T scenarios	227.08 (416.59)	200 (0)
	Unlimited at \$5/tCO ₂ vs. all SCO ₂ T scenarios	227.08 (416.59)	200 (0)
	Unlimited at \$0/tCO ₂ vs. all SCO ₂ T scenarios	493.64 (516.67)	137.2 (70.55)
	Baseline SCO ₂ T vs. other SCO ₂ T scenarios	133.44 (217.86)	97.04 (60.28)
2050 Average CO ₂ Emission Rate [gCO ₂ /kWh] (Supplementary Figure S10)	Unlimited at \$20/tCO ₂ vs. all SCO ₂ T scenarios	27.65 (53.29)	13.13 (23.47)
	Unlimited at \$5/tCO ₂ vs. all SCO ₂ T scenarios	27.65 (53.29)	13.13 (23.47)
	Unlimited at \$0/tCO ₂ vs. all SCO ₂ T scenarios	40.45 (55.29)	22.82 (24.61)
	Baseline SCO ₂ T vs. other SCO ₂ T scenarios	11.63 (20.85)	6.98 (11.66)

^aSection 5 of the SI includes details on how this metric was calculated.

these baseline assumptions may still have non-zero grid-level effects, depending on the CO₂ policy and the specific grid-level result.

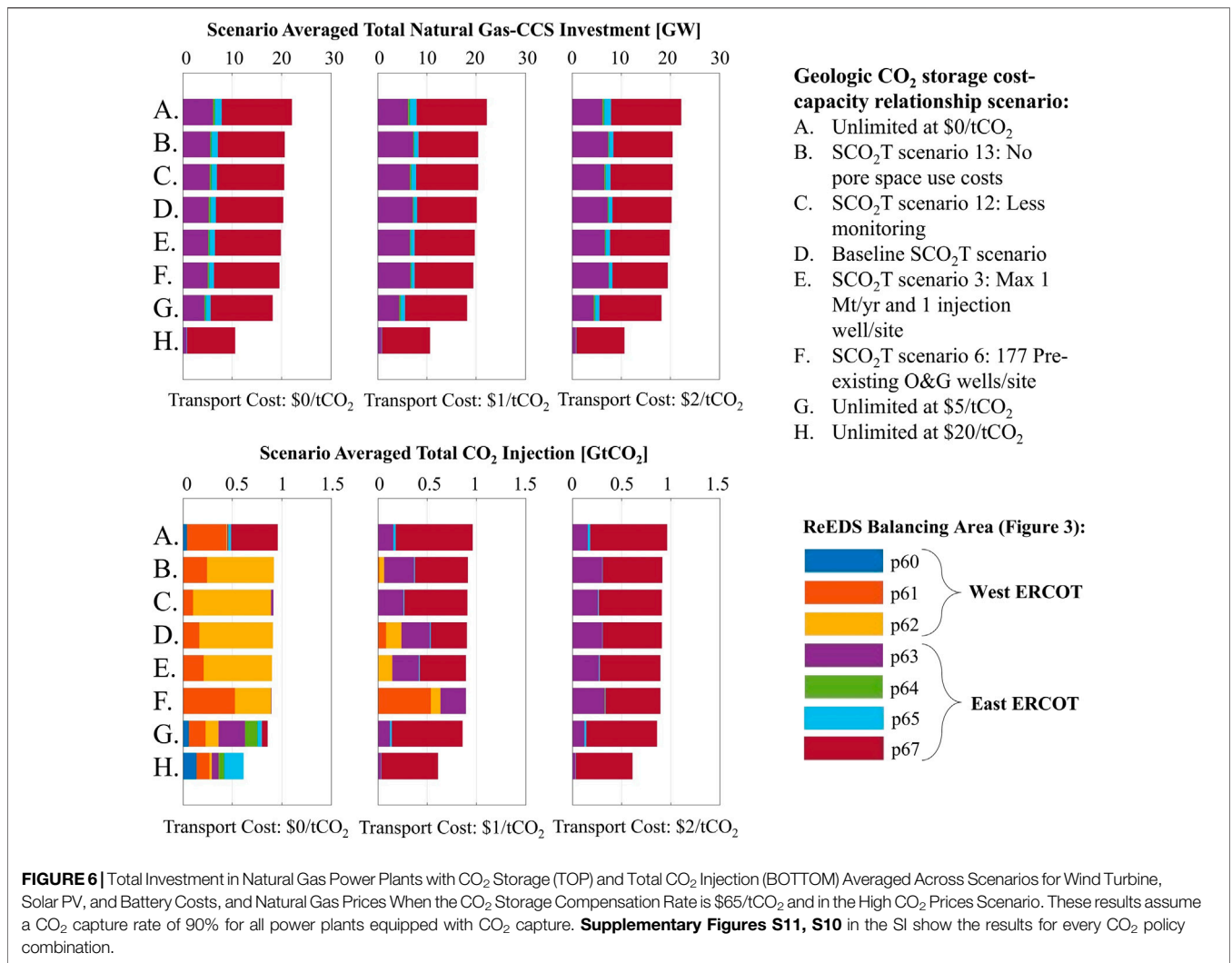
Sensitivity to CO₂ Transportation Cost

Figure 6 shows the total investment of natural-gas power plants with CO₂ capture and the total CO₂ injection, averaged across all scenarios of wind turbine, solar PV, and battery costs, and natural gas prices, in the high CO₂ prices scenario and when the CO₂ storage compensation rate is \$65/tCO₂.

Similar to **Figure 5**, **Figure 6** and the accompanying Figures in the SI suggest the cost of CO₂ transportation can affect deployment capacity decisions (e.g., on average, differences of up to about 500 MW of natural-gas power plants with CO₂ capture and up to about 0.1 GtCO₂ of total CO₂ injected), especially when CCS is marginally competitive. But this relationship is less general compared to the changes that occur in the deployment location. As shown in **Figure 6** and **Supplementary Figures S11, S12**, on average, the cost of CO₂ transportation has less effect on the location of investment in natural-gas power plants with CO₂ capture and more effect on the location of geologic CO₂ storage. Power plant capacity is built in

East ERCOT primarily because that is where most electricity is demanded. When CO₂ transportation is free, the captured CO₂ from these power plants is transported from the eastern balancing areas to the least expensive geologic CO₂ storage resources in West ERCOT. But on average, less CO₂ is transported across ERCOT when the CO₂ transportation cost is \$1/tCO₂, and no transportation occurs when the cost is \$2/tCO₂, which is possible because there are orders of magnitude more storage resources available than needed across all ERCOT balancing areas (**Figure 2; Figure 5**). Therefore, our findings primarily suggest that when there is bountiful geologic storage available and CCS is more than marginally competitive on cost, the grid-level result that is most affected by the cost of CO₂ transportation is the location of geologic CO₂ storage.

Figure 6 also suggests that the site-level factors that influence the cost and capacity of a geologic CO₂ storage site can affect the location of geologic CO₂ storage. In other words, site-level assumptions can change the cost or capacity of geologic CO₂ storage differently, depending on the geologic CO₂ storage resource, and these differences may influence the optimal location of CO₂ injection. For example, when the price of CO₂ is not zero and the CO₂ transportation cost is \$1/tCO₂, more CO₂



is injected in balancing areas p61 and p62, and less in p67, when the SCO₂T supply curves from the 177 pre-existing oil and gas wells scenario (labeled as F.) are used compared to other SCO₂T supply curve scenarios. This difference occurs because the cost of geologic CO₂ storage increases more in that SCO₂T scenario for the geologic CO₂ storage resources located in p67 compared to those in other balancing areas (Supplementary Figure S13). This finding further demonstrates the importance of studying these site-level factors and their impact on geologic CO₂ storage costs and optimal injection locations.

CONCLUSION, IMPLICATIONS, AND FUTURE WORK

Conclusion

We present the first study to our knowledge that 1) develops supply curves for geologic CO₂ storage across an energy system as large as ERCOT that are based on dynamic reservoir simulation; 2) investigates how those supply curves may change based on site-

level assumptions; and 3) quantifies the effect that CO₂ transportation and geologic storage assumptions may have on a variety of energy system planning tool results. Given the current status-quo of CO₂ transportation and geologic storage representation in energy system planning tools, our study is conducted to provide guidance to future energy system modelers by investigating what effects a more robust representation of CCS has on electric sector planning outcomes. For this reason, we interpret our results generally, so our findings apply as broadly to energy systems as possible. We find that:

1. Site-level assumptions (e.g., number of monitoring wells per injection well) may increase or decrease the cost of geologic CO₂ storage by up to a few dollars per tonne of CO₂ (similar order of magnitude as geologic variations) and can change the cost differently in different locations (Figure 2; Supplementary Figure S13).
2. The assumed cost of geologic CO₂ storage has generally small effects at the grid-level compared to other inputs (e.g., natural

gas price) (Figure 5), but these effects may be non-negligible when policy renders CCS marginally competitive (Figure 4; Table 4). When power plants with CO₂ capture are only marginally competitive on cost, the grid-level results can be sensitive enough to the cost of geologic CO₂ storage that site-level assumptions have non-zero effects on the results (Table 4).

3. When power plants with CO₂ capture are only marginally competitive on cost, overestimating the cost of geologic CO₂ storage (e.g., \$5/tCO₂) generally produces more similar grid-level results to using SCO₂T supply curves compared to assuming sequestration is free (Table 4).
4. Specific to ERCOT, there are orders of magnitude more capacity for geologic CO₂ storage available than is needed by the electricity system (Figure 2; Figure 5). In this situation, the cost of CO₂ transportation generally affects where geologic CO₂ storage investment occurs more than how much generation investment occurs or where that generation investment occurs (Figure 3; Figure 6).

Implications for Future Energy System Modelers

In general, the appropriateness of robustly representing, or not representing, any component of the energy system depends on the reason an energy system planning tool is being used, and our findings suggest CCS representation is no exception. As a result, there are situations in which current assumptions around CO₂ transportation and geologic CO₂ storage are likely sufficient, and there are other situations where they are insufficient. Based on our conclusions, we provide three recommendations for future researchers considering CCS representation in their modeling efforts:

- Energy system modelers should primarily be concerned about CO₂ transportation and geologic storage representations if they are modeling scenarios in which CCS is marginally competitive. Our findings suggest the assumed costs of CO₂ transportation and geologic storage are less consequential at the grid level if policies that incentivize decarbonization are not being investigated (e.g., CO₂ storage compensation rate of \$0/tCO₂ and no CO₂ price), or if enough policy support exists that CCS is more than marginally competitive on cost (e.g., CO₂ storage compensation rate of \$65/tCO₂ and high CO₂ prices).
- Until more geologic CO₂ storage sites are deployed that can guide site-level assumptions, future researchers concerned with robustness across uncertainty in site-level factors should consider using supply curves produced with baseline SCO₂T inputs because the baseline inputs produce comparatively “average” supply curves that are aligned with cost estimates from actual CO₂ storage sites. At the very least, our results suggest that assuming a cost for geologic CO₂ storage (e.g., \$5/tCO₂) may be less consequential than assuming a zero cost by excluding it from the model.
- A more robust characterization of CO₂ transportation in energy planning tools may not be necessary in studies

primarily concerned with capacity investment decisions across areas with many low-cost geologic CO₂ storage resources. This implication is particularly important for energy systems planning tools that model continent-scale, if not global-scale, energy systems (e.g., IAMs).

Study Limitations and Suggestions for Future Work

While our conclusions and recommendations are grounded in a very large parameter space of scenarios, they are dependent on our assumptions. Relaxing or changing these limitations is outside the scope of this study but could be the focus of future work. Key suggestions include:

- *Investigate scenarios with a lower assumed cost of CO₂ capture.* We incorporate future projections for low-cost wind turbines, solar PV, and battery energy storage technologies into our ReEDS parameter space but not for power plants with CO₂ capture because these future costs are not available as default ReEDS inputs in the 2019 version. Lowering the cost of CO₂ capture would make CCS more competitive on cost, thus, modeling lower CO₂ capture costs could decrease the importance of robustly representing geologic CO₂ storage, depending on the region and scenarios under investigation.
- *Investigate locations with less geologic CO₂ storage capacity and locations with less favorable wind and solar energy resources.* While our ERCOT case study is well endowed with high-quality wind energy, solar energy, and geologic CO₂ storage resources, there are other locations where this is not the case. Under decarbonization policy scenarios, it is likely that the cost of geologic CO₂ storage would have less of an effect on grid-level results in locations with poor wind and solar energy resources because there would be few alternatives to investing in CCS processes. Additionally, CO₂ transportation costs would likely play a larger role in investment capacity decisions in locations with less geologic CO₂ storage potential. If warranted, a more robust representation of CO₂ transportation could be achieved by iterating an energy system planning tool with SimCCS (Middleton and Bielicki, 2009; Middleton et al., 2020c), which can be used to determine optimal CO₂ pipeline networks.
- *Investigate scenarios in which bioenergy power plants with CO₂ capture (BECCS) are also available to be deployed.* While outside the scope of this study, it is increasingly understood that negative emission technologies like BECCS could play a key role in addressing climate change (Fuss et al., 2018; Minx et al., 2018; National Academies of Sciences, 2019; Fuss and Johnsson, 2021). It is likely that scenarios exist in which this technology is only marginally competitive on cost because its deployment is dependent on strong policy support, like fossil-fuel power plants with CO₂ capture. As a result, robustly representing geologic CO₂ storage could be important for such future work.

DATA AVAILABILITY STATEMENT

The only new data that this study generated were the creation of supply curves for the ERCOT region. The supply curve data generated for this study can be found in the on GitHub: https://github.com/GEG-ETHZ/ReEDS/tree/main/reeds_and_sco2t. Additionally, the primary General Algebraic Modeling System (GAMS) files that were modified for this study to add CO₂ transportation and geologic storage to ReEDS have also been deposited to the same GitHub repository. These GAMS files complement the full description of the ReEDS modifications that are included in the **Supplementary Material**.

AUTHOR CONTRIBUTIONS

JO-H: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Data curation, Writing—Original Draft, Visualization. SC: Conceptualization, Methodology, Resources, Writing—Review and Editing, Visualization. RK: Software, Resources, Writing—Review and Editing. KE: Writing—Review and Editing. MS: Writing—Review and Editing, Funding Acquisition. JB: Writing—Review and Editing. RM: Conceptualization, Resources, Writing—Review and Editing, Visualization, Funding Acquisition.

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SUPPLEMENTARY MATERIAL

The Supplementary Material for this article can be found online at: <https://www.frontiersin.org/articles/10.3389/fenrg.2022.855105/full#supplementary-material>

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