frontiers | Frontiers in Energy Research

ORIGINAL RESEARCH
published: 08 April 2022
doi: 10.3389/fenrg.2022.855105

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

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**Specialty section:**
This article was submitted to Carbon Capture, Utilization and Storage,
a section of the journal Frontiers in Energy Research

**Received:** 14 January 2022
**Accepted:** 25 February 2022
**Published:** 08 April 2022

**Citation:**
Ogland-Hand JD, Cohen SM, Kammer RM, Ellett KM, Saar MO, Bennett JA and Middleton RS (2022) The Importance of Modeling Carbon Dioxide Transportation and Geologic Storage in Energy System Planning Tools. Front. Energy Res. 10:855105. doi: 10.3389/fenrg.2022.855105

Energy system planning tools suggest that the cost and feasibility of climate-stabilizing energy transitions are sensitive to the cost of $CO_2$ capture and storage processes (CCS), but the representation of $CO_2$ transportation and geologic storage in these tools is often simple or non-existent. We develop the capability of producing dynamic-reservoir-simulation-based geologic $CO_2$ storage supply curves with the Sequestration of $CO_2$ Tool ($SCO_2T$) and use it with the ReEDS electric sector planning model to investigate the effects of $CO_2$ 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 $CO_2$ storage may be as low as \$3/t$CO_2$ and that site-level assumptions may affect this cost by several dollars per tonne. At the grid level, the cost of geologic $CO_2$ 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 $CO_2$ transportation generally affects the location of geologic $CO_2$ storage investment more than the quantity of $CO_2$ 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 $CO_2$ storage (e.g., \$5/t$CO_2$) 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 ($CO_2$), 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 |
| $SCO_2T$ | 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 $CO_2$ emission limit or a $CO_2$ price that increases the cost of technologies that emit $CO_2$ 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 $CO_2$ 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, $CO_2$ 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 $GtCO_2$ 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 $GtCO_2$/yr of $CO_2$ 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 $CO_2$ 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 $CO_2$ storage site influence its capacity and cost but are always uncertain. These properties also vary geospatially, which means the capacity and cost of geologic $CO_2$ storage can vary substantially by location. Moreover, the capacity and cost of geologic $CO_2$ 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 $CO_2$ injection rate, thus the $CO_2$ 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 $CO_2$ storage sites in existence for which to base site-level assumptions.

Additionally, representing CCS in energy system planning tools also requires assumptions about $CO_2$ transportation because it is possible to transport captured $CO_2$ long distances, via pipeline for example, before subsurface injection. The geologic $CO_2$ storage formations below any given power plant, if any exist, may or may not be the least-cost location to

**TABLE 2 |** Representation of $CO_2$ 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 $CO_2$ 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\$/t$CO_2$] | 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 |

[a]*Most recent estimates published from the tools which are used in National Energy Modeling System (NEMS) (National Energy Technology Laboratory, 2019).*
[b]*Increases to \$6.98/t$CO_2$ 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 $CO_2$ 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 $CO_2$ when considering the geospatial variability of $CO_2$ storage capacities and costs, the cost of $CO_2$ transportation, and other costs like electricity transmission infrastructure (Hannon and Esposito, 2015). Further, determining a least-cost $CO_2$ transportation network is non-trivial, even if all the $CO_2$ 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 $CO_2$ transportation endogenously within an energy system planning tool is even more difficult because the power plants equipped with $CO_2$ capture (i.e., the $CO_2$ 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 $CO_2$ capture as a technology option, but most do not represent $CO_2$ transportation or geologic storage in any way. This exclusion is typically justified by assuming that 1) the cost of $CO_2$ capture drives investment decisions because it accounts for the largest share of CCS-related costs and/or 2) the capacity and cost of geologic $CO_2$ 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 $CO_2$ 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 $CO_2$ 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—$CO_2$ 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 $CO_2$ transportation and geologic storage over entire regions (Zelek et al., 2012; National Energy Technology Laboratory, 2019); or assuming a $CO_2$ pipeline of constant length and diameter for a given power plant type to estimate $CO_2$ 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/t$CO_2$.

## 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 $CO_2$ storage and 2) using these curves to

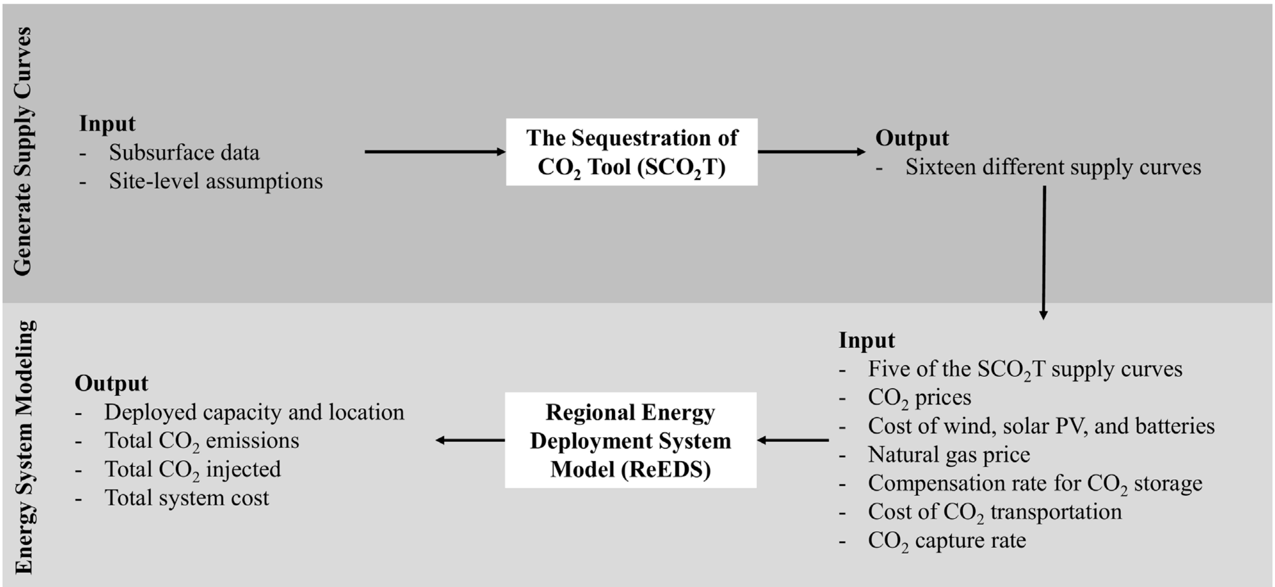


**FIGURE 1 |** Framework for quantifying the effect that $CO_2$ transportation and geologic storage assumptions could have on energy system planning tool results.

investigate the grid-level ramifications, such as deployment decisions and $CO_2$ emissions, of $CO_2$ 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 $CO_2$ 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 $CO_2$ storage using volumetric approaches to estimate $CO_2$ storage capacity. Volumetric-based assessments use algebraic equations to estimate the capacity of a potential $CO_2$ storage site (i.e., multiply the pore volume of the rock by the density of $CO_2$ and an assumed "efficiency" coefficient). In contrast, our method is based on an entirely different and novel way of estimating the capacity of $CO_2$ 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 $CO_2$ storage (Anderson, 2017; Vikara et al., 2017; Middleton et al., 2020b), but how site-level factors may affect the cost and capacity of geologic $CO_2$ storage has, to our knowledge, not been previously investigated.

Additionally, we are the first to quantify the effect that $CO_2$ transportation and geologic storage assumptions could have on a variety of energy system planning tool results (e.g., $CO_2$ 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, $CO_2$ 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 $CO_2$ Tool ($SCO_2T$) (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 $SCO_2T$ (Middleton et al., 2020a).

$SCO_2T$ is an Excel-based tool that estimates the capacity and cost of a geologic $CO_2$ storage site given underlying geologic properties. To do this, $SCO_2T$ uses reduced-order models that replicate full-physics dynamic reservoir simulations (Chen et al., 2020). We modify $SCO_2T$ by 1) adding all site-level costs from the Environmental Protection Agency (EPA) geologic $CO_2$ storage cost model (Environmental Protection Agency, 2010); 2) adding an Excel MACRO to generate supply curves; and 3) removing areas from the $SCO_2T$ subsurface dataset that prior work suggests cannot be developed for geothermal power plants or geologic $CO_2$ storage sites (Young et al., 2019; Hoover et al., 2020). Below we list some assumptions made to apply the EPA cost model for $SCO_2T$ 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 $SCO_2T$: total injection capacity [$MtCO_2$/yr] and number of $CO_2$ injection wells [wells/site]. $SCO_2T$ estimates the $CO_2$ 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 $SCO_2T$ 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 $CO_2$ 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 $CO_2$ injection pumps. We assume the downhole pressure is 80% of the lithostatic pressure (this is the maximum downhole pressure allowable within $SCO_2T$ to eliminate potential of the formation fracturing from $CO_2$ 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 $CO_2$ 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 $CO_2$ 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 $CO_2$ 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 $CO_2$ that could be geologically stored; 2) incorporate $CO_2$ transportation; and 3) account for the cost of $CO_2$ transportation and geologic $CO_2$ storage. While it is possible that sequestered $CO_2$ 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 $CO_2$ leakage in this study. Below we list a few of the key assumptions made to implement $CO_2$ 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 $CO_2$ 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 $CO_2$ storage.
- We conservatively require ReEDS to deploy enough geologic $CO_2$ storage capacity to hold the $CO_2$ that would be captured over a 30-year power plant lifetime at a 100% capacity factor.
- We follow ReEDS convention and linearly interpolate $CO_2$ captured in-between model years to estimate the amount of $CO_2$ 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 $CO_2$ 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 $CO_2$ storage infrastructure in the United States is in Texas for enhanced oil recovery.

We execute our study in two parts. First, we run $SCO_2T$ 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 $SCO_2T$ 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 $CO_2$ 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 $CO_2$ capture rate is 90% (default capture rate in ReEDS), but only for a portion of the geologic $CO_2$ storage cost-capacity relationship when the $CO_2$ 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 $CO_2$ 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 SI) | We use five of the sixteen $SCO_2T$ 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 |

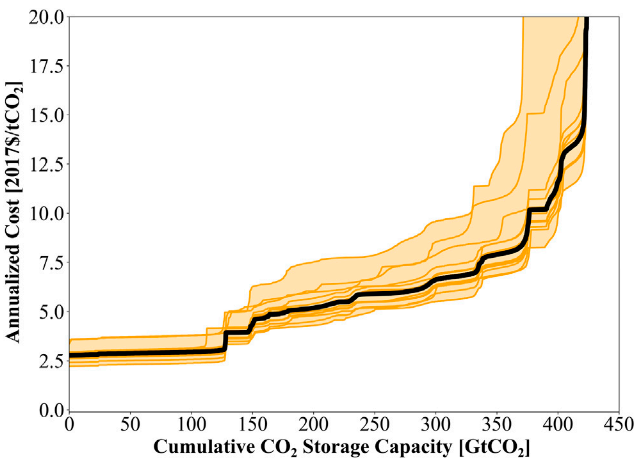


**FIGURE 2 |** Supply Curve Variability Across All Sixteen $SCO_2T$ Scenarios. The black curve is the baseline $SCO_2T$ scenario, and the orange curves and area cover the range of how costs and capacities may change based on different site level assumptions. See **Supplementary Figure S3** in the SI for $SCO_2T$ 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 $CO_2$ storage scenarios in ReEDS within a larger electricity system analysis framework. Overall, we run 2,592 distinct combinations in ReEDS of different cost, price, $CO_2$ 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 $CO_2$ Storage Supply Curves Produced With $SCO_2T$

To our knowledge, **Figure 2** shows the first supply curve for geologic $CO_2$ 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 $CO_2$ storage in ERCOT at low cost. For example, approximately 350 $GtCO_2$ (30% of the possible 1,200 $GtCO_2$ global maximum capacity needed (Rogelj et al., 2018)) of geologic $CO_2$ storage capacity is available in ERCOT at or below \$8/$tCO_2$, and approximately 100 $GtCO_2$ of this capacity is available at or below \$3/$tCO_2$. 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 $CO_2$ storage projects that suggest that the cost of geologic $CO_2$ storage is likely between \$2/$tCO_2$ and \$4/$tCO_2$ (Riestenberg et al., 2017; Holubnyak and Dubois, 2018).

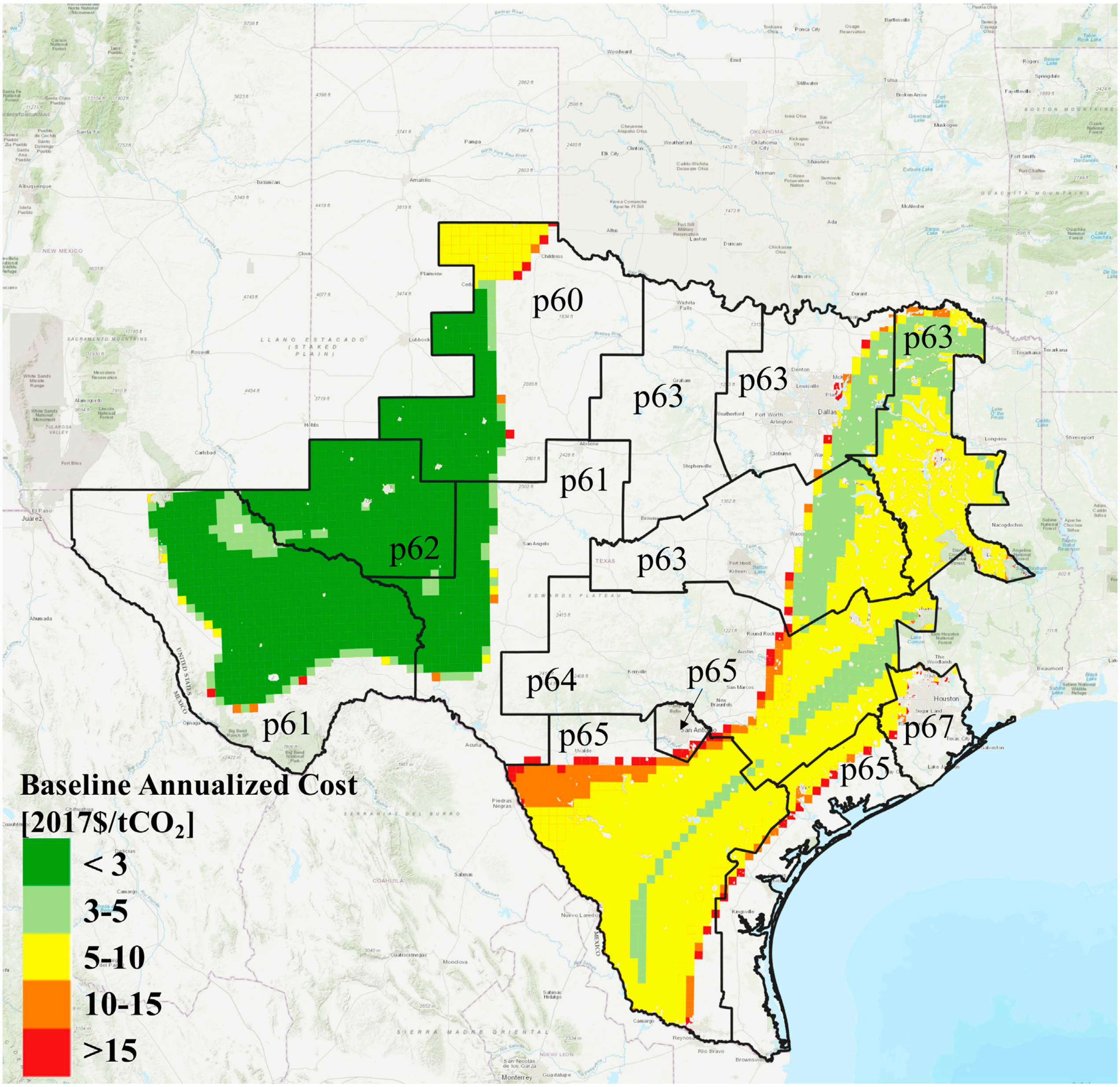


**FIGURE 3 |** Annualized Cost of Geologic $CO_2$ Storage in ERCOT for the Baseline $SCO_2T$ Inputs Scenario. The numbered labels (e.g., p61) are the ReEDS balancing areas and the black lines indicate the boundaries of wind and concentrating power resource regions that may be within a given balancing area (National Renewable Energy Laboratory, 2019a).

**Figure 2** also demonstrates that the site-level assumptions influencing the cost of geologic $CO_2$ storage can change costs by a few dollars per $tCO_2$, which is not negligible considering that the costs are only around $3/$tCO_2$ for the least expensive 100 $GtCO_2$ of capacity. Further, when compared against our prior work that demonstrates that reservoir depth, porosity, and thickness can change costs by ~$2/$tCO_2$, ~$4/$tCO_2$, or ~$5/$tCO_2$, 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 $SCO_2T$ inputs (black line) provide cost estimates that are intermediate to cost estimates from the more extreme $SCO_2T$ 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

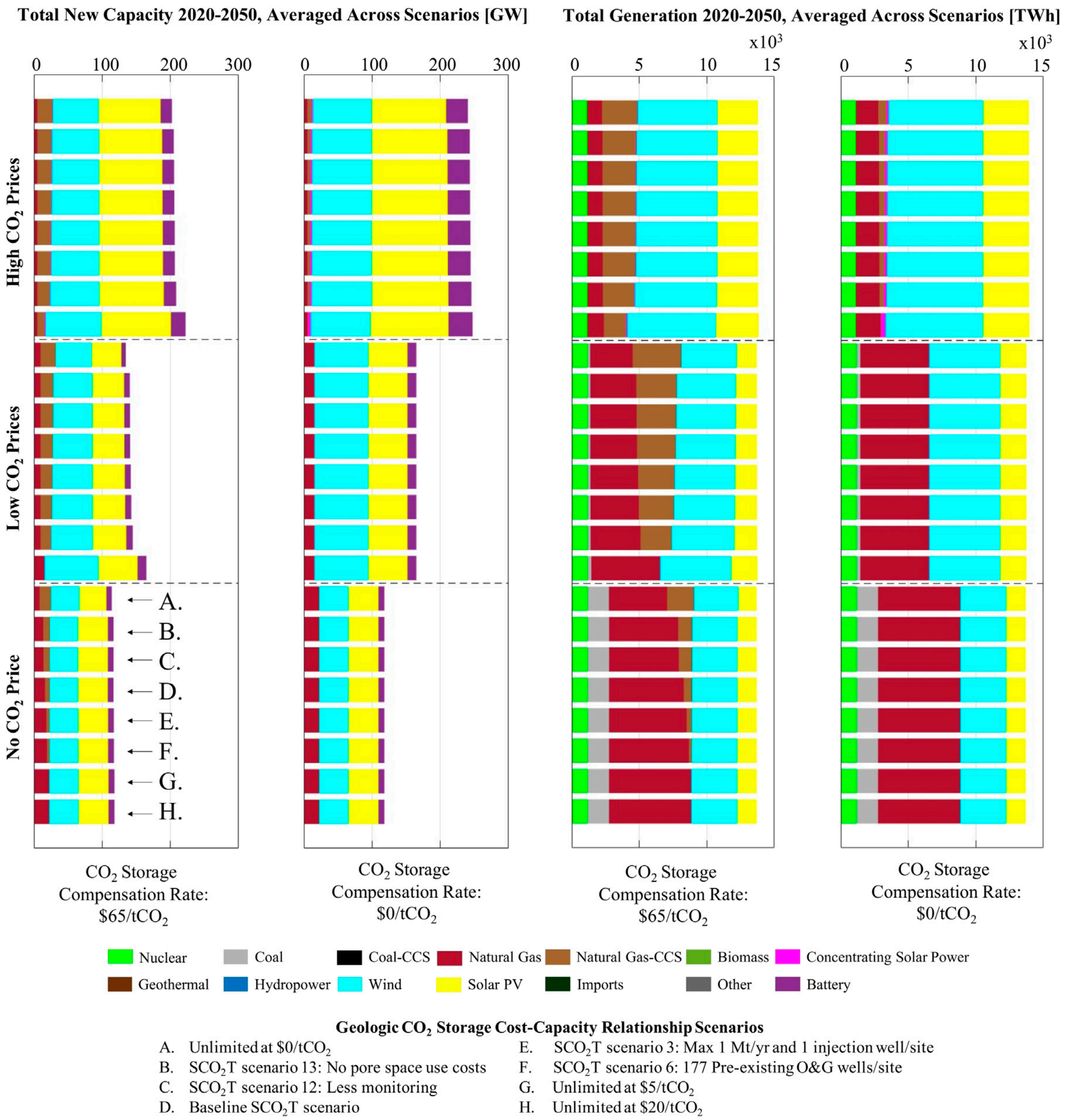


**FIGURE 4 |** Total New Capacity and Generation 2020–2050 Averaged Across Scenarios for Wind Turbine, Solar PV, and Battery Costs, Natural Gas Prices, and $CO_2$ Transportation Costs. These results assume a $CO_2$ capture rate of 90% in all power plants equipped with $CO_2$ capture. In each combination of $CO_2$ policy (e.g., no $CO_2$ price that increases the cost of emitting $CO_2$ and a \$0/t$CO_2$ $CO_2$ storage compensation rate), the $SCO_2T$ supply curve scenarios follow the same A.–H. order of increasing cost.

work use baseline $SCO_2T$ inputs for $CO_2$ storage supply curves until there are more geologic $CO_2$ storage projects deployed that can be used to guide site-level assumptions.

**Figure 3** shows the geospatial distribution of geologic $CO_2$ storage costs across ERCOT using the baseline $SCO_2T$ input scenario. There are geologic $CO_2$ 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 $CO_2$ 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 $SCO_2T$ enables. For example, the NEMS-CTS model uses an estimated cost of geologic $CO_2$ storage of \$9/t$CO_2$ (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 $SCO_2T$ cost estimates, it would be difficult to know that this estimate is arguably not representative of costs in Texas.

## Grid-Level Effects of $CO_2$ 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 $CO_2$ transportation costs for each combination of $CO_2$ policy and $CO_2$ 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 $CO_2$ policies and geologic $CO_2$ 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 $CO_2$ storage (Section 3.2.1) and $CO_2$ transportation (Section 3.2.2).

Across all combinations of $CO_2$ policy and geologic $CO_2$ 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 $CO_2$ policy combinations is solar PV and wind turbines. No coal power plants with $CO_2$ capture are deployed and the deployment of natural-gas power plants with $CO_2$ capture is highly reliant on $CO_2$ policies. Natural-gas power plants with $CO_2$ capture are generally deployed at comparable capacities, if not less, than new natural-gas power plants without $CO_2$ capture. More general discussion about these general results, including what services power plants with $CO_2$ capture provide, is included in Section 6.2 of the SI.

The results in **Figure 4** demonstrate that the assumed cost of geologic $CO_2$ 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 $CO_2$ policy renders natural gas power plants with $CO_2$ capture less expensive (e.g., geologic $CO_2$ storage compensation rate of \$65/t$CO_2$ and high $CO_2$ prices) or more expensive (e.g., geologic $CO_2$ storage compensation rate of \$0/t$CO_2$ and low $CO_2$ prices) relative to other energy technologies, the average investment and average generation become relatively insensitive to the assumed cost of geologic $CO_2$ storage. In contrast, when the $CO_2$ policy renders natural gas power plants with $CO_2$ capture only marginally competitive on cost (e.g., geologic $CO_2$ storage compensation rate of \$65/t$CO_2$ and no $CO_2$ price), small increases to the assumed cost of geologic $CO_2$ storage (e.g., <\$1/t$CO_2$) can result in large changes to investment or generation because other energy technologies (i.e., natural gas without $CO_2$ 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 $CO_2$ capture to $CO_2$ policy occurs because the $CO_2$ policy combination determines when natural gas power plants with $CO_2$ capture compete closely with other energy technologies.

### Sensitivity to Geologic $CO_2$ Storage Cost

**Figure 5** shows the variability of total $CO_2$ injected across every combination of $CO_2$ prices, wind, solar PV, and battery costs, natural gas prices, $CO_2$ transportation costs, cost of geologic $CO_2$ storage, and $CO_2$ capture rate that we considered when the compensation rate for geologic $CO_2$ storage is \$65/$CO_2$. 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 $CO_2$ capture (**Supplementary Figure S6**); total investment in wind and solar energy technologies (**Supplementary Figure S7**); total $CO_2$ emissions (**Supplementary Figure S8**); total system cost (**Supplementary Figure S9**); and 2050 average $CO_2$ emission rate (**Supplementary Figure S10**).

First, **Figure 5** suggests that for our scenario assumptions, there are orders of magnitude more capacity for geologic $CO_2$ storage in ERCOT than needed by the electricity system. For example, a maximum of about 2.8 Gt$CO_2$ are cumulatively injected by 2050, which is approximately 2.4% of the total geologic $CO_2$ storage capacity available in ERCOT at or below \$5/t$CO_2$ (**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., $CO_2$ policy, the price of natural gas) than to the cost of geologic $CO_2$ storage. For example, when the compensation rate for storing $CO_2$ is \$65/t$CO_2$ in the low $CO_2$ prices scenario, the amount of $CO_2$ injected during any given geologic $CO_2$ storage cost scenario varies between approximately 0.5 Gt$CO_2$ and 2.5 Gt$CO_2$, depending on the price of natural gas and the cost of solar PV, wind, and batteries. Similarly, changes in the assumed power plant $CO_2$ capture rate generally result in smaller changes to other grid-level results compared to the $CO_2$ 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 $CO_2$ storage, the cost of geologic $CO_2$ storage was the only input that could eliminate $CO_2$ injection in some policy combinations (e.g., when the geologic $CO_2$ storage compensation rate was \$65/t$CO_2$ in the low $CO_2$ prices scenario). This finding is important to highlight because, like the other cost and price scenarios, all geologic $CO_2$ 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 $CO_2$ capture by overestimating the cost of geologic $CO_2$ 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 $CO_2$ storage cost scenarios when the

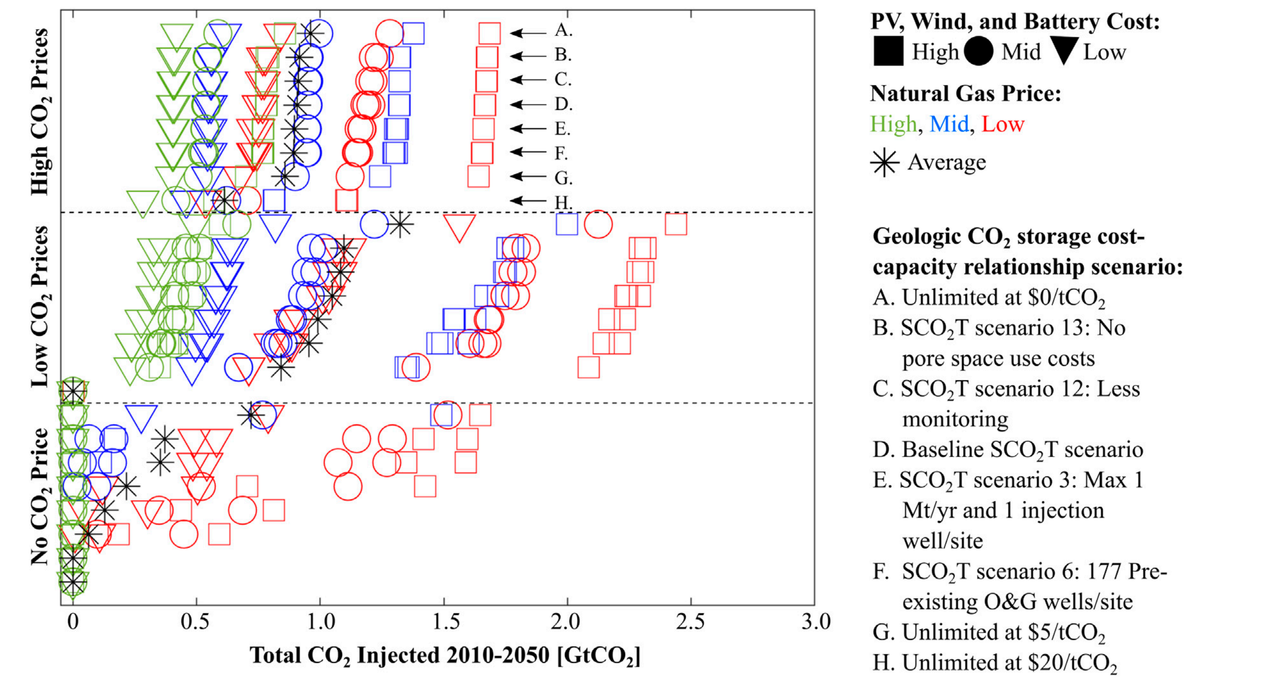


**FIGURE 5 |** Total $CO_2$ Injected Across Model Horizon When $CO_2$ Storage Compensation Rate is $65/t$CO_2$. Within a given geologic $CO_2$ cost-capacity relationship scenario (i.e., row of data), differences between data points that have the same shape and color (e.g., red squares) are due to the different $CO_2$ transportation costs: $0/t$CO_2$, $1/t$CO_2$, and $2/t$CO_2$ (**Table 3**). These results assume a $CO_2$ capture rate of 90% for any power plant equipped with $CO_2$ capture. See the SI for results across all scenarios (**Supplementary Figure S5**).

$CO_2$ compensation rate was $65/t$CO_2$ and no $CO_2$ 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 $CO_2$ 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 $CO_2$ 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 $CO_2$ capture and total amount of $CO_2$ injected, the grid-level result that is most sensitive to the assumed cost of $CO_2$ storage is the 2050 average $CO_2$ emission rate. This occurs because natural-gas power plants without $CO_2$ capture are deployed instead of natural-gas power plants with $CO_2$ capture as the assumed cost of geologic $CO_2$ storage increases (**Figure 4**). In turn, the grid-level result that is least sensitive to the cost of $CO_2$ storage in this $CO_2$ policy combination is the total investment in wind and solar energy technologies because as the cost of $CO_2$ storage increases, the natural gas power plants with $CO_2$ 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 $CO_2$ storage representation may not substantially influence results.

**Table 4** also suggests that it may be less consequential to overestimate the cost of geologic $CO_2$ storage compared to assuming it is free: the mean and standard deviations between the $0/t$CO_2$ cost scenario and the five $SCO_2T$ supply curve scenarios (third row in each section of **Table 4**) are generally larger compared to the mean and standard deviations between the $20/t$CO_2$ or $5/t$CO_2$ cost scenarios and the five $SCO_2T$ supply curve scenarios (first and second rows in each section of **Table 4**). This result occurs in this $CO_2$ policy scenario because natural-gas power plants with $CO_2$ capture are deployed when the cost of geologic $CO_2$ storage is $0/t$CO_2$, but there are some $SCO_2T$ supply curve scenarios that render natural-gas power plants with $CO_2$ capture non-competitive on cost compared to natural-gas power plants without $CO_2$ capture (**Figure 4**). As a consequence, when $SCO_2T$ supply curve scenarios are used, the grid-level results are more similar to when geologic $CO_2$ storage is assumed to cost $20/t$CO_2$ or $5/t$CO_2$ than $0/t$CO_2$. This finding suggests that if $SCO_2T$ supply curves cannot be used, overestimating the cost of geologic storage (i.e., $5/t$CO_2$) 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 $SCO_2T$ supply curve cost scenario and the four other $SCO_2T$ 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 $CO_2$ storage are closer across this comparison, but these differences are non-zero. As a result, while we suggest future work use the baseline $SCO_2T$ 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 $CO_2$ Storage Cost-Capacity Scenarios When $CO_2$ Storage Compensation Rate is \$65/t$CO_2$ in the No $CO_2$ Price Scenario: Mean (Standard Deviation in Parentheses). These results are for a $CO_2$ capture rate of 90%. All differences are between the same combination of inputs (e.g., natural gas price). The "all $SCO_2T$ scenarios" refers to the five $SCO_2T$ 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 $SCO_2T$ scenario (labeled D in **Figure 5**) and the other four $SCO_2T$ 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/t$CO_2$ vs. all $SCO_2T$ scenarios | 6.82 (11.86) | 200 (0) |
| | Unlimited at \$5/t$CO_2$ vs. all $SCO_2T$ scenarios | 6.82 (11.86) | 200 (0) |
| | Unlimited at \$0/t$CO_2$ vs. all $SCO_2T$ scenarios | 9.71 (11.52) | 124.29 (73.55) |
| | Baseline $SCO_2T$ vs. other $SCO_2T$ scenarios | 2.65 (4.28) | 75.52 (65.39) |
| Wind and Solar Energy Technology Investment [GW] (**Supplementary Figure S7**) | Unlimited at \$20/t$CO_2$ vs. all $SCO_2T$ scenarios | 1.6 (3.08) | 2.25 (4.17) |
| | Unlimited at \$5/t$CO_2$ vs. all $SCO_2T$ scenarios | 1.6 (3.08) | 2.25 (4.17) |
| | Unlimited at \$0/t$CO_2$ vs. all $SCO_2T$ scenarios | 4.36 (5.7) | 5.18 (5.63) |
| | Baseline $SCO_2T$ vs. other $SCO_2T$ scenarios | 0.67 (1.53) | 0.98 (1.81) |
| Total $CO_2$ Emissions [Gt$CO_2$] (**Supplementary Figure S8**) | Unlimited at \$20/t$CO_2$ vs. all $SCO_2T$ scenarios | 0.18 (0.34) | 3.27 (6.28) |
| | Unlimited at \$5/t$CO_2$ vs. all $SCO_2T$ scenarios | 0.18 (0.34) | 3.27 (6.28) |
| | Unlimited at \$0/t$CO_2$ vs. all $SCO_2T$ scenarios | 0.38 (0.43) | 7.19 (7.49) |
| | Baseline $SCO_2T$ vs. other $SCO_2T$ scenarios | 0.11 (0.18) | 2.04 (3.49) |
| Total System Cost [2017\$B][a] (**Supplementary Figure S9**) | Unlimited at \$20/t$CO_2$ vs. all $SCO_2T$ scenarios | 18.47 (33.33) | 3.15 (5.61) |
| | Unlimited at \$5/t$CO_2$ vs. all $SCO_2T$ scenarios | 18.47 (33.33) | 3.15 (5.61) |
| | Unlimited at \$0/t$CO_2$ vs. all $SCO_2T$ scenarios | 24.35 (29.66) | 3.88 (4.6) |
| | Baseline $SCO_2T$ vs. other $SCO_2T$ scenarios | 9.42 (16.03) | 1.56 (2.62) |
| Total $CO_2$ Injected [Mt$CO_2$] (**Figure 5**) | Unlimited at \$20/t$CO_2$ vs. all $SCO_2T$ scenarios | 227.08 (416.59) | 200 (0) |
| | Unlimited at \$5/t$CO_2$ vs. all $SCO_2T$ scenarios | 227.08 (416.59) | 200 (0) |
| | Unlimited at \$0/t$CO_2$ vs. all $SCO_2T$ scenarios | 493.64 (516.67) | 137.2 (70.55) |
| | Baseline $SCO_2T$ vs. other $SCO_2T$ scenarios | 133.44 (217.86) | 97.04 (60.28) |
| 2050 Average $CO_2$ Emission Rate [g$CO_2$/kWh] (**Supplementary Figure S10**) | Unlimited at \$20/t$CO_2$ vs. all $SCO_2T$ scenarios | 27.65 (53.29) | 13.13 (23.47) |
| | Unlimited at \$5/t$CO_2$ vs. all $SCO_2T$ scenarios | 27.65 (53.29) | 13.13 (23.47) |
| | Unlimited at \$0/t$CO_2$ vs. all $SCO_2T$ scenarios | 40.45 (55.29) | 22.82 (24.61) |
| | Baseline $SCO_2T$ vs. other $SCO_2T$ scenarios | 11.63 (20.85) | 6.98 (11.66) |

[a]*Section 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 $CO_2$ policy and the specific grid-level result.

## Sensitivity to $CO_2$ Transportation Cost

**Figure 6** shows the total investment of natural-gas power plants with $CO_2$ capture and the total $CO_2$ injection, averaged across all scenarios of wind turbine, solar PV, and battery costs, and natural gas prices, in the high $CO_2$ prices scenario and when the $CO_2$ storage compensation rate is \$65/t$CO_2$.

Similar to **Figure 5**, **Figure 6** and the accompanying Figures in the SI suggest the cost of $CO_2$ transportation can affect deployment capacity decisions (e.g., on average, differences of up to about 500 MW of natural-gas power plants with $CO_2$ capture and up to about 0.1 Gt$CO_2$ of total $CO_2$ 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 $CO_2$ transportation has less effect on the location of investment in natural-gas power plants with $CO_2$ capture and more effect on the location of geologic $CO_2$ storage. Power plant capacity is built in East ERCOT primarily because that is where most electricity is demanded. When $CO_2$ transportation is free, the captured $CO_2$ from these power plants is transported from the eastern balancing areas to the least expensive geologic $CO_2$ storage resources in West ERCOT. But on average, less $CO_2$ is transported across ERCOT when the $CO_2$ transportation cost is \$1/t$CO_2$, and no transportation occurs when the cost is \$2/t$CO_2$, 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 $CO_2$ transportation is the location of geologic $CO_2$ storage.

**Figure 6** also suggests that the site-level factors that influence the cost and capacity of a geologic $CO_2$ storage site can affect the location of geologic $CO_2$ storage. In other words, site-level assumptions can change the cost or capacity of geologic $CO_2$ storage differently, depending on the geologic $CO_2$ storage resource, and these differences may influence the optimal location of $CO_2$ injection. For example, when the price of $CO_2$ is not zero and the $CO_2$ transportation cost is \$1/t$CO_2$, more $CO_2$

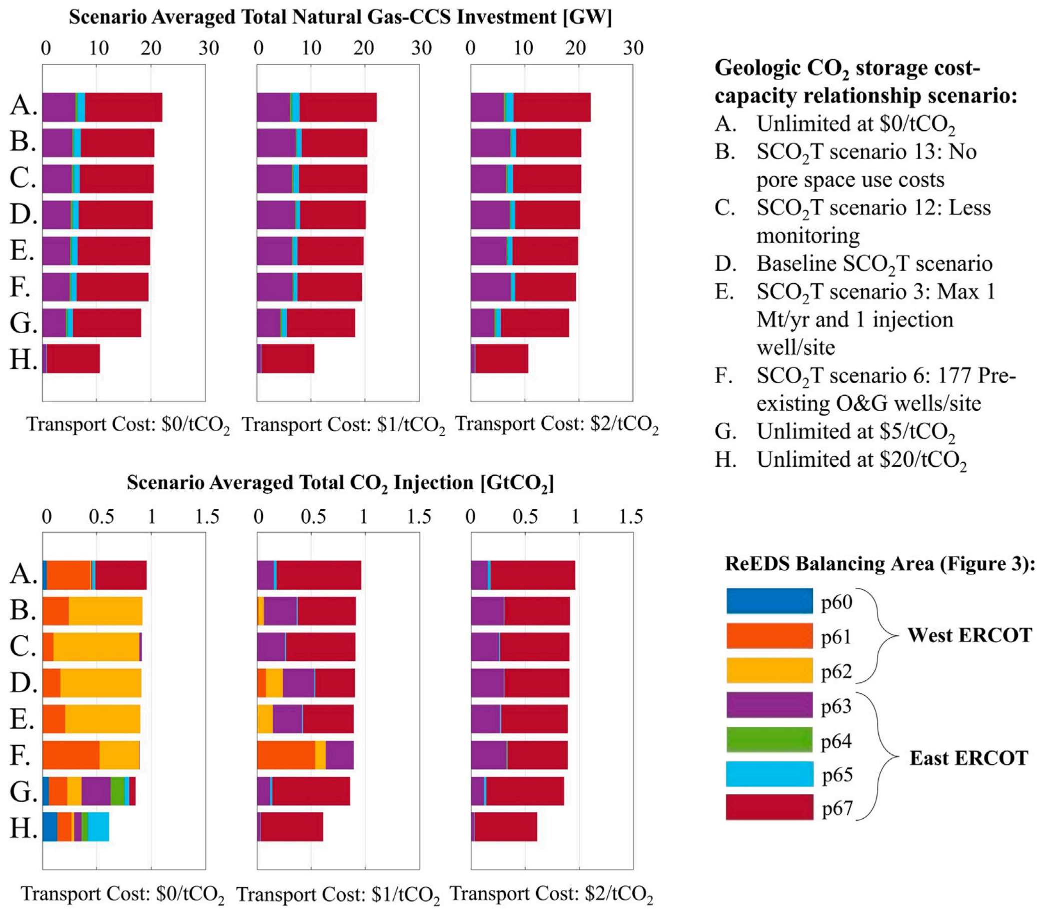


**FIGURE 6 |** Total Investment in Natural Gas Power Plants with $CO_2$ Storage (TOP) and Total $CO_2$ Injection (BOTTOM) Averaged Across Scenarios for Wind Turbine, Solar PV, and Battery Costs, and Natural Gas Prices When the $CO_2$ Storage Compensation Rate is \$65/t$CO_2$ and in the High $CO_2$ Prices Scenario. These results assume a $CO_2$ capture rate of 90% for all power plants equipped with $CO_2$ capture. **Supplementary Figures S11, S10** in the SI show the results for every $CO_2$ policy combination.

is injected in balancing areas p61 and p62, and less in p67, when the $SCO_2T$ supply curves from the 177 pre-existing oil and gas wells scenario (labeled as F.) are used compared to other $SCO_2T$ supply curve scenarios. This difference occurs because the cost of geologic $CO_2$ storage increases more in that $SCO_2T$ scenario for the geologic $CO_2$ 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 $CO_2$ 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 $CO_2$ 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 $CO_2$ transportation and geologic storage assumptions may have on a variety of energy system planning tool results. Given the current status-quo of $CO_2$ 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 $CO_2$ storage by up to a few dollars per tonne of $CO_2$ (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 $CO_2$ 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 $CO_2$ capture are only marginally competitive on cost, the grid-level results can be sensitive enough to the cost of geologic $CO_2$ storage that site-level assumptions have non-zero effects on the results (**Table 4**).

3. When power plants with $CO_2$ capture are only marginally competitive on cost, overestimating the cost of geologic $CO_2$ storage (e.g., \$5/t$CO_2$) generally produces more similar grid-level results to using $SCO_2T$ supply curves compared to assuming sequestration is free (**Table 4**).
4. Specific to ERCOT, there are orders of magnitude more capacity for geologic $CO_2$ storage available than is needed by the electricity system (**Figure 2**; **Figure 5**). In this situation, the cost of $CO_2$ transportation generally affects where geologic $CO_2$ 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 $CO_2$ transportation and geologic $CO_2$ 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 $CO_2$ transportation and geologic storage representations if they are modeling scenarios in which CCS is marginally competitive. Our findings suggest the assumed costs of $CO_2$ transportation and geologic storage are less consequential at the grid level if policies that incentivize decarbonization are not being investigated (e.g., $CO_2$ storage compensation rate of \$0/t$CO_2$ and no $CO_2$ price), or if enough policy support exists that CCS is more than marginally competitive on cost (e.g., $CO_2$ storage compensation rate of \$65/t$CO_2$ and high $CO_2$ prices).
- Until more geologic $CO_2$ 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 $SCO_2T$ inputs because the baseline inputs produce comparatively "average" supply curves that are aligned with cost estimates from actual $CO_2$ storage sites. At the very least, our results suggest that assuming a cost for geologic $CO_2$ storage (e.g., \$5/t$CO_2$) may be less consequential than assuming a zero cost by excluding it from the model.
- A more robust characterization of $CO_2$ transportation in energy planning tools may not be necessary in studies primarily concerned with capacity investment decisions across areas with many low-cost geologic $CO_2$ 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 $CO_2$ 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 $CO_2$ capture because these future costs are not available as default ReEDS inputs in the 2019 version. Lowering the cost of $CO_2$ capture would make CCS more competitive on cost, thus, modeling lower $CO_2$ capture costs could decrease the importance of robustly representing geologic $CO_2$ storage, depending on the region and scenarios under investigation.
- *Investigate locations with less geologic $CO_2$ 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 $CO_2$ storage resources, there are other locations where this is not the case. Under decarbonization policy scenarios, it is likely that the cost of geologic $CO_2$ 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, $CO_2$ transportation costs would likely play a larger role in investment capacity decisions in locations with less geologic $CO_2$ storage potential. If warranted, a more robust representation of $CO_2$ 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 $CO_2$ pipeline networks.
- *Investigate scenarios in which bioenergy power plants with $CO_2$ 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 $CO_2$ capture. As a result, robustly representing geologic $CO_2$ 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.


## FUNDING

Martin Saar thanks the Werner Siemens Foundation (Werner Siemens-Stiftung, WSS) for its support of the Geothermal Energy and Geofluids (GEG) group (GEG.ethz.ch) at ETH Zurich. ETH Zurich is also thanked for its support of the GEG group. This material is also based upon work supported by the U.S. Department of Energy, Office of Science, Small Business Innovations Research program under Award DE-SC0021570. The content is solely the responsibility of the authors and does not necessarily represent the official views of the Werner Siemens Foundation, ETH Zurich, or the U.S. Department of Energy.

## ACKNOWLEDGMENTS

Many thanks to Isamu Naets for all the computer and python support required to get ReEDS up and running at ETH Zurich.


## 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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**Conflict of Interest:** Authors JO-H, KE, JB, and RM were employed by the company Carbon Solutions LLC.
The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.