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Natural Gas in the U.S. Southeast Power Sector under Deep Decarbonization: Modeling Technology and Policy Sensitivities

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Abstract

Concerns over climate change, along with falling costs of renewable energy technologies, have led to increased scrutiny over the role of natural gas in a low-carbon energy future. In this study, we use a multi-stage capacity expansion modeling framework to evaluate the role of natural gas-fired power plants (NG) in the evolving electrical grid of the U.S. Southeast. Under assumptions of perfect foresight and high electrification, our modeling considers cost-optimal grid operations, investments, and retirements through 2045 using a detailed representation of the U.S. Southeast's electrical grid which includes inter-region transmission, variable renewable energy resource characteristics, brownfield capacity, and lifetime and economic retirements. We explore the impact of key technology and policy sensitivities including three alternative CO_2 emissions trajectories, technology costs, nuclear plant lifetime extensions, upstream methane emissions, and direct regulations of NG deployment and financing. In addition to the unprecedented deployments of variable renewable energy and battery storage necessary to decarbonize, we find that investments in NG are made across all scenarios evaluated. Results highlight the substantial emissions contributions of the existing coal fleet and the potential for emissions reductions if lower-carbon generation resources, including new NG with and without carbon capture and storage, can replace this capacity. Furthermore, emissions limits which require the lowest mid-century CO_2 emissions do not necessarily lead to the greatest cumulative emissions reductions over the planning horizon. Finally, we observe that large differences in technology and policy conditions result in only modest changes in capacity deployments and the cost of the energy transition, allowing utilities and regulators to move forward with confidence under a strategy primarily characterized by phasing out coal generation and deploying new renewable energy. These results support nuanced approaches to resource planning for future low-carbon grids which consider both short-term and long-term trade-offs of cost and emissions reductions.

1 Introduction

In recent years, the electric power sector in the U.S. has reduced its reliance on coal (2013 TWh generation in 2005 to 965 TWh in 2019, 50% of total generation to 23%) in favor of increasing generation from natural gas (NG, 761 TWh to 1586 TWh, 19% to 38%) and variable renewable energy (VRE) sources, namely wind and solar (18 TWh to 403 TWh, $\leq$1% to 10%).[1] This has contributed to a 32% reduction in power sector CO_2 emissions, with the shift from coal to gas alone accounting for 65% of this reduction, relative to 2005 levels.[2] Currently, NG power plants are the primary source of flexible generation in managing the temporal variability in VRE generation. This is most evident in regions like California, where, as the share of solar generation has increased from 0.3% to 11.4% from 2009 to 2018, the operations of the NG power plant fleet has evolved to account for the diurnal pattern in solar output, leading to increased startups and ramping events.[3] At the same time, the increased penetration of VRE resources, along with low NG prices until recently, has led to depressed wholesale electricity prices, which has adversely impacted the revenues of gas generators, leading to premature retirements in some cases.[4][5] As costs of wind and solar are projected to decline further and public policy emphasizes accelerated deep decarbonization of the power sector along with economy-wide electrification, the share and magnitude of VRE generation is expected to grow substantially in the next few decades.[6][7] However, the long-term role for NG in the transition to a deeply-decarbonized power system remains uncertain due to several technology and policy factors. First, projected declines in cost for lithium-ion battery storage resources [8] could improve the cost-effectiveness of their use in balancing mismatch the between VRE generation and electricity demand over increasing time-scales (e.g., intra-day to inter-day). Second, potential developments and associated cost reductions in long-duration energy storage could mitigate the need for dispatchable, low-carbon generation as part of deep decarbonization scenarios.[9][10] Similarly, developments in low-carbon dispatchable generation technologies using NG in conjunction with pre-combustion (e.g., H_2) or post-combustion carbon capture and storage (CCS) could create a role for NG in a deeply decarbonized power grid. Third, while many U.S. states and utilities have committed to 100% decarbonization of the power sector by mid-century, the evolution of policy in the interim period remains less well-defined. Moreover, there is growing interest in minimizing investment in new fossil-fuel infrastructure to minimize potential for stranded assets.[11] Finally, there is growing recognition about potentially under-counted fugitive methane emissions from the NG supply chain and their near-term radiative forcing impacts, which suggests greater climate risks associated with NG deployment than previously thought.[12][13] Here, we use a multi-stage capacity expansion modeling framework to study the role for new and existing NG resources in the transition to a deeply decarbonized electricity sector by mid-century, under alternative technology and policy assumptions inspired by the uncertainty factors highlighted above.

There is a growing body of academic literature focusing on low-carbon power grid scenarios using various capacity expansion models (CEMs), but only a handful of papers have centrally evaluated the role of both existing and new NG generation under varying regulatory, policy, and financial assumptions. **Sepulveda et al. (2018)** evaluate optimal resource portfolios across numerous technological uncertainties. They explore several low CO_2 emissions intensity scenarios, including fully-decarbonized cases, and find that the availability of firm, low-carbon generation resources, such as NG combined cycle (NGCC) power plants with CCS and nuclear power, reduce costs 10-62% across fully-decarbonized scenarios without these resources. When firm, low-carbon resources are not included, NG capacity without CCS is built across scenarios with emissions intensities as low as 1 gCO_2 per kilowatt-hour (kWh).[7] **Mignone et al. (2017)** use the National Energy Modeling System (NEMS) U.S. energy system model with foresight to evaluate the effect of a rising future price of CO_2 on investments in new NG capacity before 2030. They find no material effect on new NG deployment before 2030 under varying carbon pricing cases. However, their modeling excludes energy storage resources, which are expected to be an important part of a VRE-dominant grid.[14] **Babaee and Loughlin (2018)** use the MARKet ALocation (MARKAL) U.S.-wide energy systems optimization model to explore the role of NGCC power plants with CCS from 2005 to 2055 under alternative moderate emissions reductions scenarios and other technology and cost sensitivities. Though they do not explore deeply decarbonized systems, they find that NGCC provides substantial generation along explored emissions reductions pathways in the short-term and mid-term with the exception of runs with high natural gas prices, and that a substantial portion of this capacity is retrofit with CCS in the long-term. Additionally, they find the methane leakage rate to be the strongest factor in contributing to optimal deployment of NGCC power plants with CCS.[15] **Jayadev et al. (2020)** develop an optimization model for U.S.-wide electric sector capacity planning and explore four scenarios: a no-policy baseline, a no new transmission sensitivity, a pessimistic VRE and storage cost sensitivity, and a carbon tax sensitivity. Their results suggest five key policy insights, one of which is that "natural gas capacity growth is strong and robust, but utilization of gas capacity declines steadily and significantly."[16] Though their load duration curve methodology has limits when applied to electricity systems with high VRE penetration, **Teplin et al. (2019)** estimate that by 2035, new clean energy portfolios consisting of wind, solar, battery storage, and demand flexibility will be cheaper to build than continued operation of 90% of proposed NGCC power plants.[8]

Using a multi-stage adaptation of the GenX CEM, this study will provide several novel contributions to the growing body of knowledge surrounding the role of NG in future low-carbon electricity systems.[17] First, it is unclear the extent to which the aforementioned studies evaluate the role of NG in a highly electrified future with increasing electrification of the economy; our analysis will assume high electrification, based on consumption profiles adapted from a recent study, in order to better understand how the capacity mix responds to a growing electrical load, as would likely occur if national decarbonization goals are to be achieved.[18][19] Second, in addition to contributing further insight into commonly tested technology and policy sensitivities such as low VRE and storage costs, we will explore several policy-relevant sensitivities including the effect of nuclear plant lifetimes, accounting for upstream methane emissions for coal and NG, salvage value assumptions for new NG plants without CCS, and restrictions on construction of new NG plants without CCS. Third, there is a gap in research investigating the role for NG specifically in the transition to a deeply decarbonized, as opposed to low-carbon, energy system. While studies such as Sepulveda et al. (2018) include deep decarbonization scenarios with emissions intensities as low as 1 gCO_2/kWh and no-emissions cases, they take a "greenfield" approach which lacks inter-annual grid evolution trends or existing "brownfield" capacity.[7] Existing studies which take a multi-stage approach, such as Babaee and Loughlin (2018), fail to evaluate NG deployment under extremely low emissions scenarios.[15] By combining a multi-stage approach with multiple deep decarbonization pathways which increase in stringency over the planning horizon, this paper will shed light on how the capacity mix could evolve over time in a transition to a deeply decarbonized grid. Fourth, as a case study, we will focus on the U.S. Southeast, a region that has received little attention in the academic CEM literature, but where the model paradigm of integrated resource planning is aligned with practice. The U.S. Southeast is home to over 30 million retail electricity consumers who consumed nearly 900 TWh in 2019, accounting for 22% of national electricity generation and 20% of powers sector CO_2 emissions.[20][21][22] The rest of the paper is organized as follows. The next section describes the methodology and the case study, with further details provided in the supporting information (SI). This is followed by a description of key model results and observations. Finally, we conclude by discussing the policy implications of the findings along with summarizing the key study limitations.

2 Methods

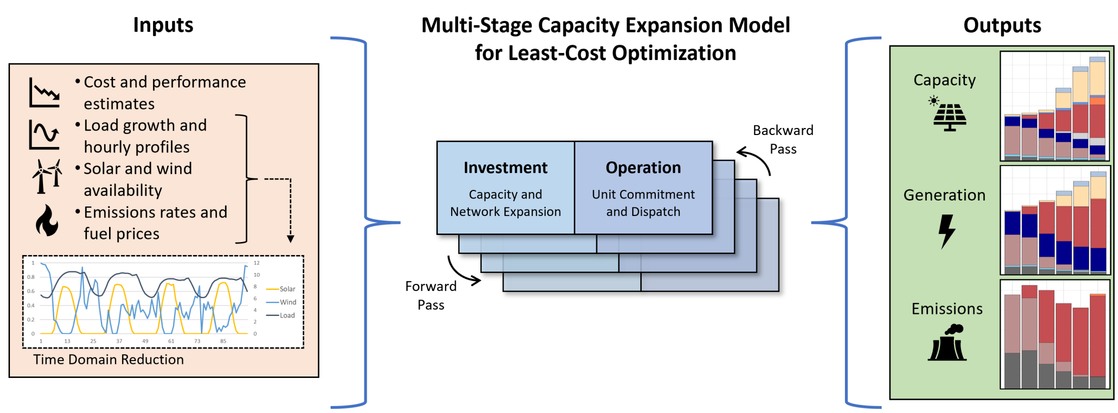

Figure 1: Our study uses an dual dynamic programming-based solution strategy to evaluate a multi-stage CEM that includes long-term planning and short-term operational decisions over six five-year investment stages under perfect foresight.

2.1 Capacity Expansion Modeling

For this analysis, we implemented multi-stage investment planning as a new feature to the open-source GenX CEM.[17] Planning for deep decarbonization with high levels of VRE deployment and evolving carbon policies suggests detailed modeling of grid operations over multiple planning stages with consideration of the turnover of existing generation assets. A multi-stage CEM also allows us to incorporate dynamic cost information and lifetime retirements for new and existing capacity. We configured the model with six five-year stages spanning 2020 to 2045, set carbon policies with mass-based emissions caps, and enabled network expansion. To be consistent with historical trends and standard planning processes, we do not model greenfield development in the first model stage, representing 2020-2025, in any scenario. We used four main strategies to enable computational tractability of the resulting multi-stage CEM. First, we configured unit commitment of thermal power plants under a linear relaxation assumption, providing a reasonable approximation of an integer unit commitment model solution while permitting the removal of computationally taxing integer variables.[23] Second, spinning and operating reserves were not modeled due to the substantial increase in memory and computational time that this requires. Third, we employed time domain reduction to represent the annual grid operations per stage using a set of fourteen representative weeks at an hourly resolution.[24] Details of this procedure are included in the SI. Fourth, we solved the multi-stage CEM by exploiting the decomposable structure of the model formulation along each stage using the well-known dual dynamic programming (DDP) algorithm as described in Lara et al. (2018).[25] In this approach, we first employ a forward pass calculation starting at the first stage that myopically evaluates least-cost investments at each stage and carries over investment/retirement decisions to the next stage. Being myopic, the forward pass produces an upper bound of the total system cost for the multi-stage CEM. This is followed by a backward pass calculation that uses information of investments in future stages to update investment decisions in previous stages. This is accomplished by adding cuts derived using the dual variables to constraints linking capacity across stages. The backward passes enables the calculation of a lower bound for the multi-stage CEM objective since it ignores capacity linking constraints between stages. Iterating between the forward pass and backward pass is carried out until the upper and lower bounds converge within a numerical value.[25][26]

Sensitivity	**ID**	**CO_2 Policy**	**VRE and Storage Costs**	**Nuclear SLTEs***	**Include Upstream Emissions in CO_2 Policy**	**Salvage Value for NG w/o CCS After 2050**	**No New NG w/o CCS After 2025**
Reference	0	None	Medium	Yes	No	Yes	No
	1	High	Medium	Yes	No	Yes	No
	2	Medium	Medium	Yes	No	Yes	No
	3	Low	Medium	Yes	No	Yes	No
Low VRE and Storage Costs	4	High	Low	Yes	No	Yes	No
	5	Medium	Low	Yes	No	Yes	No
	6	Low	Low	Yes	No	Yes	No
No Nuclear SLTEs	7	High	Medium	No	No	Yes	No
	8	Medium	Medium	No	No	Yes	No
	9	Low	Medium	No	No	Yes	No
Upstream Emissions	10	High	Medium	Yes	Yes	Yes	No
	11	Medium	Medium	Yes	Yes	Yes	No
	12	Low	Medium	Yes	Yes	Yes	No
Accelerated Depreciation	13	High	Medium	Yes	No	No	No
	14	Medium	Medium	Yes	No	No	No
	15	Low	Medium	Yes	No	No	No
Only CCS NG After 2025	16	High	Medium	Yes	No	Yes	Yes
	17	Medium	Medium	Yes	No	Yes	Yes
	18	Low	Medium	Yes	No	Yes	Yes

Table 1: List of cases evaluated in the study (rows) spanning alternative technology and policy drivers (columns). Cells in grey indicate parameters which differ from the reference scenario. *Note that SLTE stands for "second lifetime extension."

2.2 Model Scenarios

Our model scenarios span five key technology and policy drivers. These include (1) low cost projections for VRE and storage technologies based on available projections from the National Renewable Energy Laboratory's (NREL) Annual Technology Baseline (ATB),[27] (2) the allowance of second lifetime extensions (SLTEs) for nuclear power plants, (3) the inclusion of upstream greenhouse gas (GHG) emissions for coal and NG in model carbon accounting, (4) accelerated depreciation strategies for thermal power plants, and (5) a CCS requirement for new NG generation beginning in 2030. This set of technological, economic, and policy sensitivities address key elements affecting NG deployment as identified in the literature review above and introduce the novel consideration of accelerated depreciation strategies.[15][16][7] From these sensitivities, we compose a reference scenario with moderate VRE and storage costs, SLTEs granted for all existing nuclear capacity, upstream methane emissions not included in carbon policies, normal depreciation rates with salvage value for NG assets assumed beyond the model horizon, and new NG permitted after 2025 with or without CCS.

Within each sensitivity and the reference scenario, we evaluate three CO_2 emissions policies which represent different levels of deep decarbonization. In increasing order of stringency, we refer to these as the High, Medium, and Low policy cases. From 2020 through 2045, these policies incrementally reduce region-wide annual emissions from a regional baseline of 500 million tonnes (MT) to 250 MT in 2030 (all) followed by 50 (High), 25 (Medium), and 5 (Low) MT by 2045, respectively (see Table S1). These amount to 90%, 95% and 99% CO_2 emissions reduction compared to 2007 regional maximums.

2.3 Data

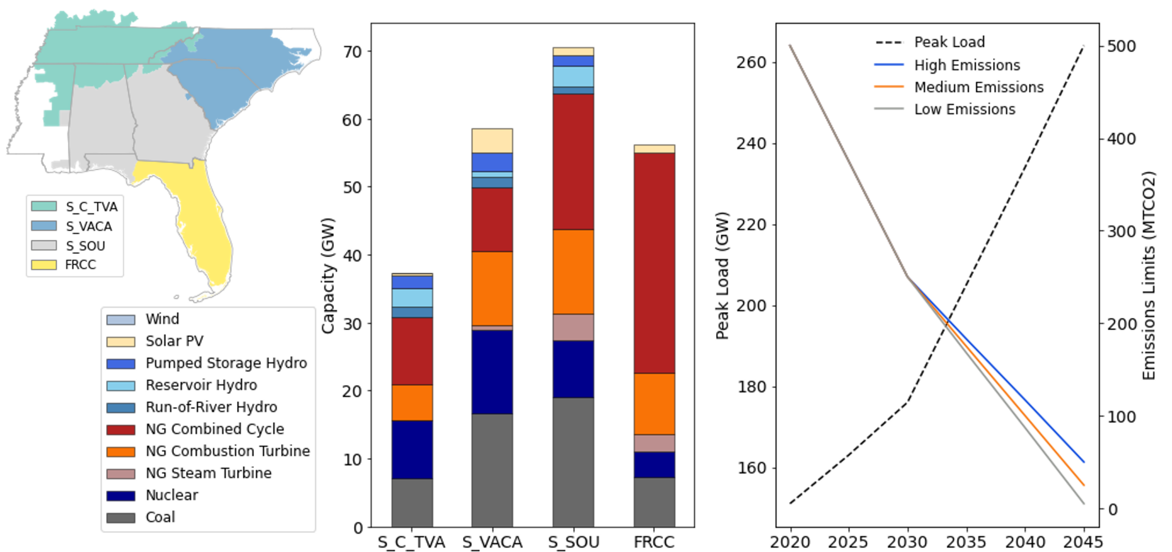

Figure 2: Geographic boundaries of the Southeast model (upper left), brownfield capacities (GW) of each of the four respective model regions (center), and peak load (GW) and annual emissions limits (MT) across the three CO_2 policy scenarios for each of the six five-year model periods.

We model the U.S. Southeast power system considering four model regions adapted from the Environmental Protection Agency's (EPA) Power Sector Modeling Platform v6 (IPM model) [28] – S_C_TVA, S_VACA, S_SOU, and FRCC, as shown in Figure 2. These four regions include parts of the seven Southeastern states outside of wholesale power markets.

The existing, or "brownfield," generating capacity as of 2018 of these four model regions is approximately 23% coal, 52% NG, 15% nuclear, and 3% VRE. As listed in Tables S3, S4, S5, S7, and S6, brownfield resources represented by the model include conventional steam coal, natural gas combined cycle (NGCC), natural gas combustion turbine (NGCT), natural gas steam turbine (NGST), nuclear, reservoir hydroelectric, run-of-river hydroelectric, pumped hydroelectric storage (PHS), solar photovoltaic (solar PV), and onshore wind. As described in detail in the SI, cost and operational data were derived from numerous sources including the U.S. Energy Information Agency (EIA) Form EIA-860,[29] the PowerGenome data aggregation software,[30] Sepulveda et al. (2018),[7] the NREL ATB,[31] and the MIT Future of Storage Study.[32]

New, or "greenfield," generating capacity permitted by the model include NGCC, NGCT, NGCC with CCS (NGCC-CCS), nuclear, PHS, solar PV, wind, and lithium-ion battery storage (Li-ion). It is assumed that developable capacity for reservoir and run-of-river hydropower has been exhausted, and new PHS capacity is only permitted in S_C_TVA and S_SOU. Cost and operational data regarding greenfield resources are included in Tables S8, S9, S10, S11, S12, S13, S14, S15, and S16 as well as Figure S1. As described in detail in the SI, these data were derived from numerous sources including the NREL ATB,[27] software tools developed in Brown and Botterud (2020),[33] the EPA IPM model,[28] the MIT Future of Storage Study,[32] and O'Connor et al. (2016).[34] We do not permit any greenfield development in the first model stage, representing 2020-2025.

Other input data concern network topology, fuel costs, load forecasts, and VRE resource availability. With parameters summarized in Table S18, transmission was represented by inter-regional 500 kV transmission lines with maximum transfer capacities taken from the IPM model,[28] and up to 30 GW of expansion was permitted on each existing inter-zonal connection, with expansion costs and capital recovery period (40 years) adopted from the NREL ReEDs model.[35] With adjustments for geography and inter-regional power exchange as detailed in the SI, load profiles were derived from the 2018 NREL Electrification Future Study under assumptions of "High" electrification and "Moderate" technological advancement.[19] Historical capacity factor (CF) profiles were generated for solar PV and wind resources using the methodology outlined in Brown and Botterud (2020) under the assumptions of horizontal 1-axis-tracking PV for solar resources and Gamesa G126/2500 turbines at 100-meter height for wind resources.[33] Hydroelectric CF profiles were derived from the nameplate capacity and net monthly generation of hydroelectric plants in each model region as recorded in Form EIA-923 and described in the SI.[20] Other key model parameters and assumptions are summarized in Table S20. The discount rate assumed for computing the net present value of costs calculation is 4.5%.

3 Results

3.1 Reference Scenario

Under the reference scenario, deployments of solar PV and wind are comparable to NG deployment in the case without an emissions constraint, but VRE capacity dominates total deployment under carbon policies, accounting for 68-80% of total generation in 2045 (see Figure 3). Over the thirty-year planning horizon, the model deploys a cumulative 202-249 GW of solar PV and 143-160 GW of wind under carbon policy cases, with greater deployment occurring in scenarios with lower CO_2 emissions limits. Annual installation limits (nearly 10 and 16 GW/year for PV and wind respectively – see Table S13 in the SI) are binding for solar PV in 2035 across all CO_2 emission scenarios. For context, the resulting 2035 annual average deployment rates of 10 GW/y for solar PV and 6-9 GW/year for wind are about comparable to or larger than the 2019 nationwide annual deployment rates of about 4 GW for solar PV and 11 GW for wind. As compared to the High policy case, the Medium and Low cases also witness earlier deployment of VRE capacity to enable increased VRE generation by the end of the model horizon. Li-ion storage deployment is limited in the unconstrained case but increases with carbon policies by 154-263%, with an average installed storage duration of 2.5-5.3 hours in 2045 across the CO_2 emissions policies.[1] The increased VRE and Li-ion storage deployments are supplemented by 4-7 GW of new transmission capacity across the three emissions-constrained scenarios, compared with only 1 GW in the unconstrained case, to connect solar deployment in FRCC and S_C_TVA with load in other regions (see regional distribution of capacity provided in Figure S4). Existing nuclear generation, with SLTEs granted for eligible plants under the reference scenario, retains its full capacity throughout the planning horizon and across all cases (unless stated otherwise), indicating the significant value of this zero-carbon baseload capacity regardless of policy. Despite this, no new nuclear capacity is deployed throughout the planning horizon, likely due to high assumed capital costs relative to competing low-carbon resources, notably VRE generation.

Under the reference scenario, new NG remains a large part of the resource mix, but increasingly strict carbon policies, which become binding starting in 2030 across all emissions constrained cases, can reduce cumulative new NG capacity by 47-64%, as shown in Figure 3. In the unconstrained case, NG without CCS still accounts for 48% of generation in 2045, but carbon policies decrease this value to 11%, 5%, and 1% in increasing order of strictness (see the 1st row of Figure 3). As CO_2 emissions limits become more constraining, NGCC with CCS is favored, resulting in 4 GW in the final stage under the Medium policy and 23 GW in the final stage under the Low policy. The evolution of the

[1] PHS is also deployed to its maximum available capacity of 7 GW in all model scenarios, only differing by the timing of its deployment.

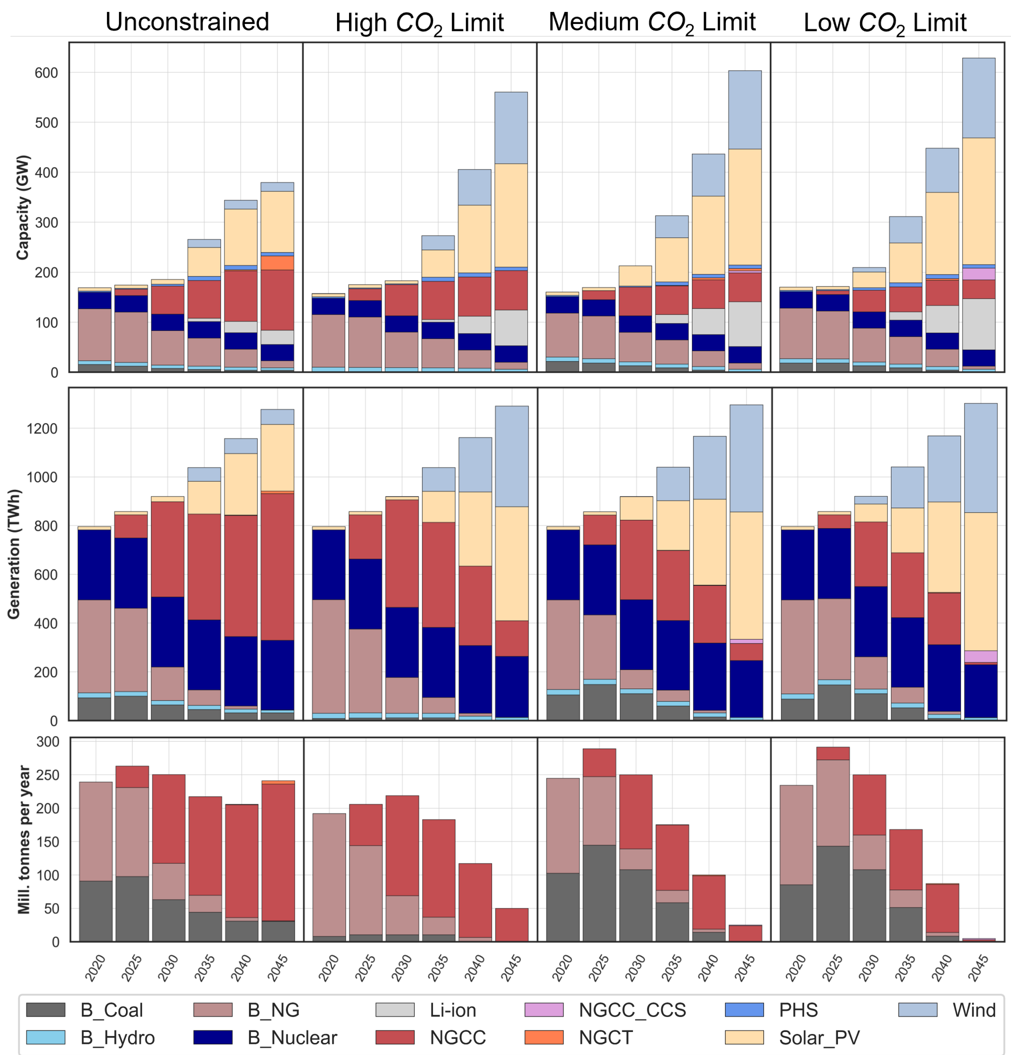

Figure 3: Reference Scenario: System-wide capacity (GW), annual generation (TWh), and annual emissions (MT) without CO_2 policies and with High, Medium, and Low policies.

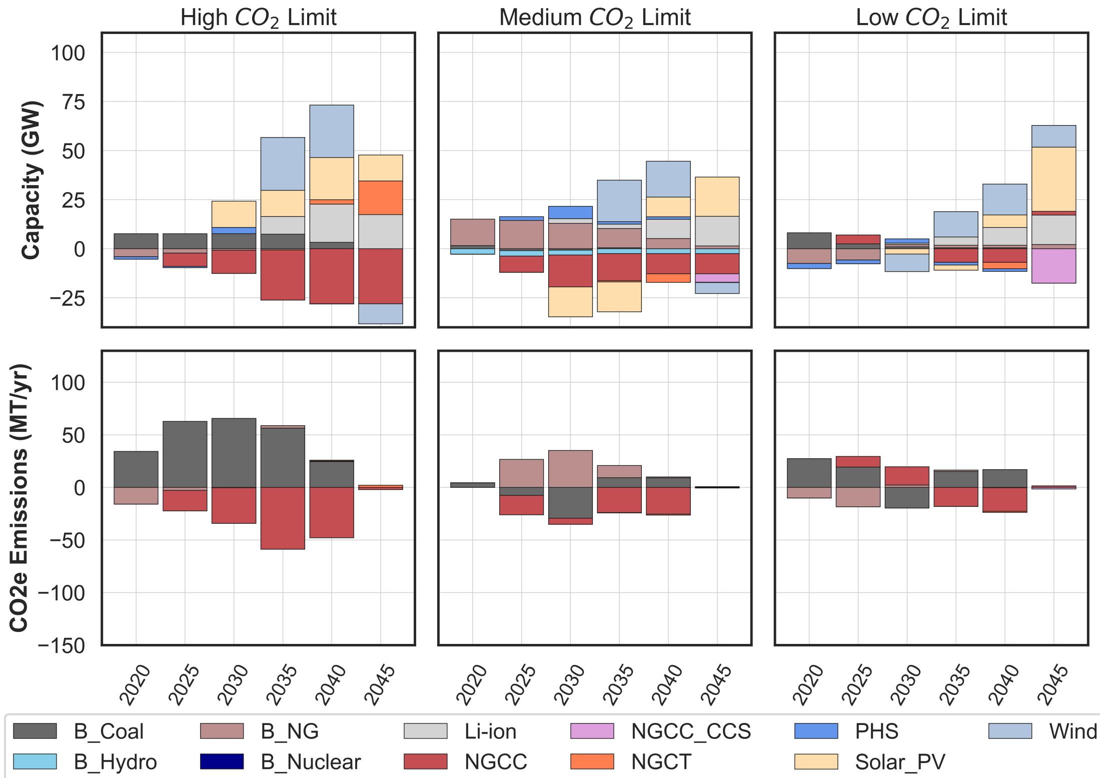

Figure 4: Low VRE and Storage Costs – Changes in system-wide capacity (GW) and annual CO_2 emissions (MT) under the High, Medium, and Low policies with respect to the reference scenario.

existing thermal generation fleet is impacted by long-term expectations of carbon policy, with coal retirements happening faster under the High policy than under the Low, due to the above-mentioned changes in new NG deployment in the early stages (2025-2035) across these scenarios. Compared to the Low policy, the High policy allows for greater use of NG generation without CCS in later investment stages, making investment in new NG in early-stages more attractive. For similar reasons, existing NG capacity is retired more slowly under the High policy compared to the Low. Overall, the trend in accelerated coal retirement and replacement with new NG contributes to the lower cumulative CO_2 emissions outcomes in the High policy as compared to Medium and Low (reductions of 2.2 gigatonnes (GT) CO_2 vs. 1.7 GT vs. 1.9 GT, or 32% vs. 24% vs. 27% compared to the unconstrained emissions case, as noted in Table 2). Correspondingly, these carbon policies increase the net present cost of the system by a relatively modest 2%, 5%, and 6% (see Table 2).

3.2 Low Cost Projections for VRE and Storage

Figure 4 shows that lower VRE and storage cost projections lead to increased cumulative deployment of solar PV compared to wind across the emissions policies, which is partly explained by the increases in Li-ion storage deployment. The average storage duration of 4.5-6.2 hours installed by 2045 in the low VRE and storage cost scenario points to the economic value of using Li-ion storage for shifting solar generation to the evening hours when demand is relatively high. Other studies have arrived at similar conclusions regarding the preferential synergy between Li-ion storage and solar PV compared to wind.[36]

Compared to reference scenario cost assumptions, low cost projections for VRE and storage to lead to reductions in cumulative new NG capacity without CCS by 14%, 17%, and 19% under the High, Medium, and Low policies, respectively. In this scenario, there is less need for CCS expansion, leading to only 6 GW of NGCC-CCS installed in 2045 under the Low policy. However, there is greater need for network expansion, with 1-4 GW more transmission deployed compared to the reference scenario. As shown in Figure 4, most of the incrementaly displaced NG capacity is replaced by more, lower-

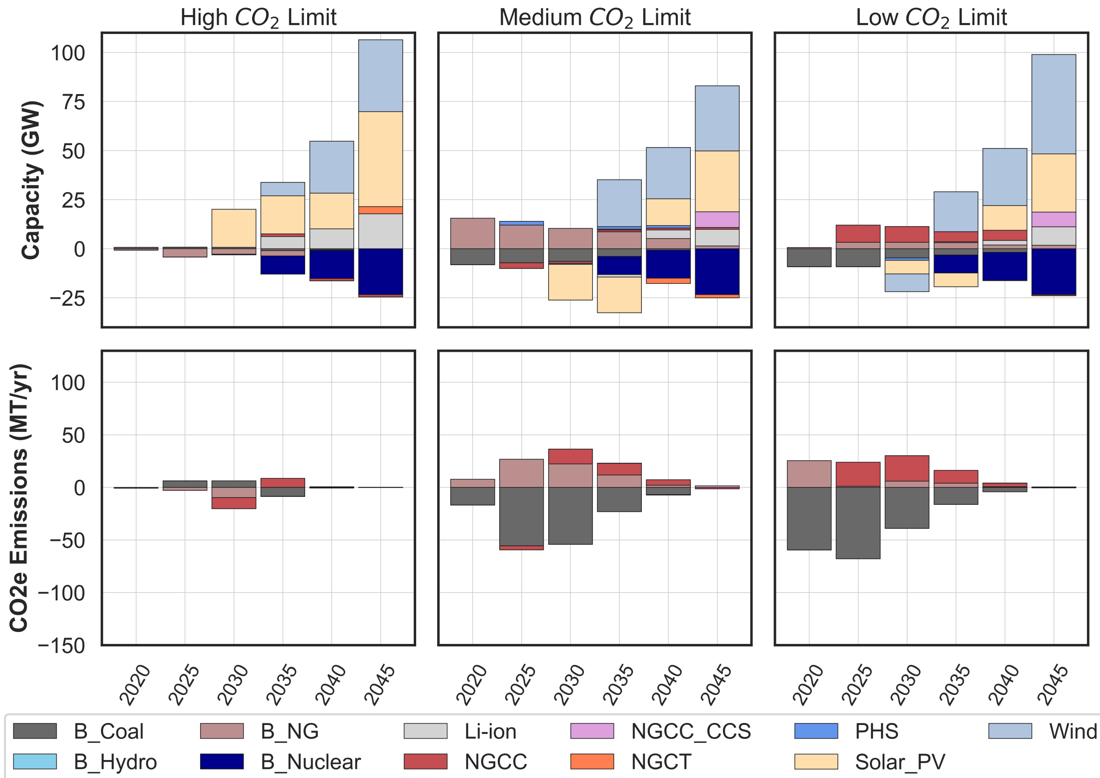

Figure 5: No Nuclear Second Lifetime Extensions – Changes in system-wide capacity (GW) and annual CO_2 emissions (MT) under the High, Medium, and Low policies with respect to the reference scenario.

cost VRE and storage, but it also encourages some extended coal use in the interim. With perfect foresight, the model anticipates increased deployment of VRE and storage capacity in future stages that discourages new NG deployment in earlier periods, which explains the extended coal use compared to the reference scenario. In fact, under High and Low policies, cumulative emissions increase by 7% and 2% compared to corresponding reference cases due to extended use of existing coal assets, whereas the Medium policy leads to extended use of existing NG instead of coal, leading to marginally lower cumulative emissions (1%). Finally, the low VRE and storage cost scenario is the only sensitivity in consideration that decreases costs with respect to the reference scenario (up to 3% across all three emissions policy cases and the no emissions policy case). However, this result is intuitive since all other scenarios impose additional constraints whereas this scenario models a reduced cost for VRE and storage deployment.

3.3 Nuclear Second Lifetime Extensions

Compared to the reference scenario, disallowing nuclear SLTEs leads to modest increases in cumulative new NG capacity without CCS (see Table 3), and leads to greater need for low-carbon dispatchable generation capacity in the form of NGCC-CCS in the later stages (0-31 GW vs. 0-23 GW NGCC-CCS). As shown in Figure 5, most of the lost nuclear capacity, which retires in the latter half of the planning horizon, is replaced by VRE and Li-ion storage. Compared to the reference scenario, cumulative solar PV capacity increases by 12-24%, wind capacity by 21-32%, and Li-ion capacity by 9-25%. At the same time, we note a shift in the thermal generation fleet towards new and existing NG over coal, particularly for 2030 and earlier, likely because the expected nuclear retirements makes incremental NG and VRE investment in these stages more attractive, thereby impacting the merit-order dispatch in these periods. Collectively, these contribute to a 2-3% increase in system cost compared to the reference scenario. At the same time, by decreasing reliance on coal in favor of NG, VRE, and storage, retirement of nuclear capacity after only one lifetime extension leads to lower cumulative emissions compared to corresponding reference cases, with reductions of 1%, 6%, and 8% from High to Low

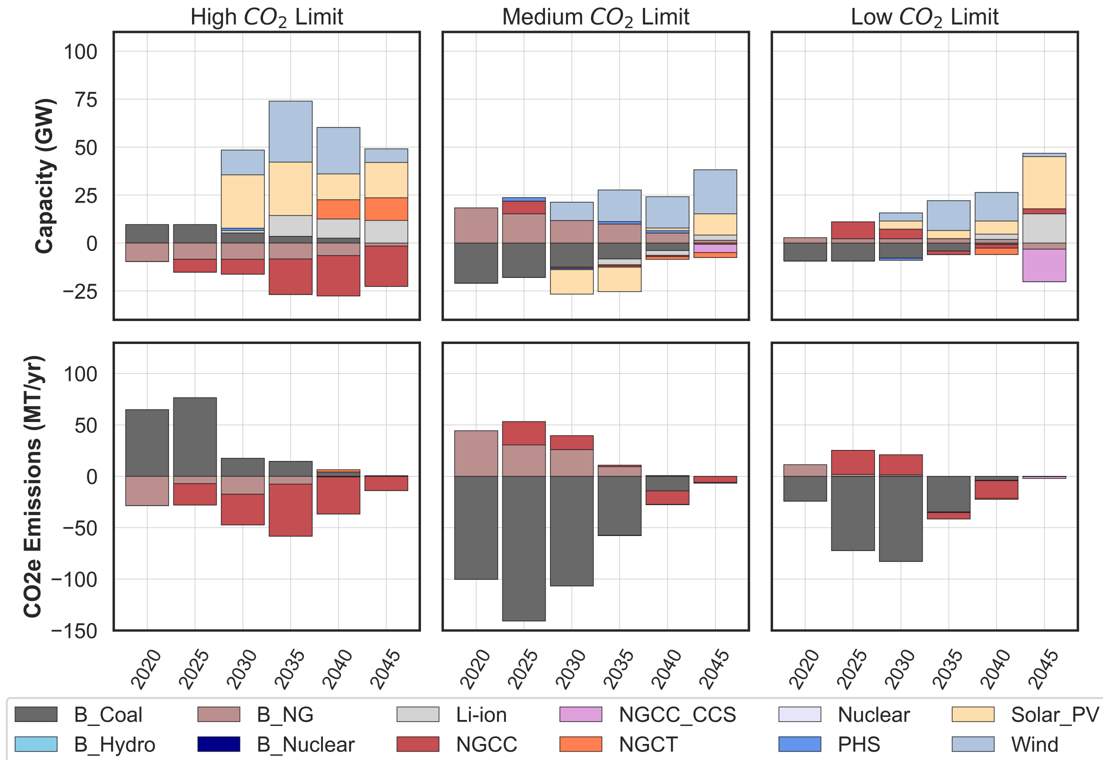

Figure 6: Including Upstream Emissions within CO_2 Limits – Changes in system-wide capacity (GW) and annual CO_2 emissions (MT) under the High, Medium, and Low policies with respect to the reference scenario.

policy.

3.4 Accounting for Upstream Emissions

In the upstream emissions scenario, we account for the non-combustion GHG emissions associated with delivering coal and NG to the power generation site in the annual sector-wide CO_2 emissions limit (see Table S2). This scenario approximates a lifecycle GHG emissions-based policy.[2] Naturally, tallying upstream GHG emissions within sectoral CO_2 emissions limits leads to reductions in cumulative new NG capacity compared to the corresponding reference cases, decreasing by 12%, 10%, and 13% from High to Low policy. Not only capacity installations but capacity utilization of NG plants are reduced, leading to a shift from higher capital cost (and high-efficiency) NGCC to lower capital cost (and lower efficiency) NGCT as the favored NG resource to be deployed, most noticeable under the High and Medium policies. At the same time, because CCS technology only curbs combustion-level emissions, NGCC-CCS deployment is also decreased, with only 12 GW installed in the final stage of the Low policy case, a decrease of 48% with respect to the Low reference case. The reduced availability of CCS under the Low policy resulted in a 2045 addition of 3 GW of new nuclear capacity, the only scenario to result in nuclear installations. As shown in Figure 6, this downward pressure on carbon emitting capacity intuitively leads to increased and earlier deployment of VRE and Li-ion storage. Compared to the reference scenario, cumulative solar PV capacity increases by 6-10%, wind capacity by 3-8%, and Li-ion capacity by 12-13%. Finally, despite considering an expanded system boundary for the sector-wide emissions constraint, combustion-related CO_2eq emissions decline by 3%, 11%, and 8% from High to Low policy compared to respective reference cases. This emission reduction incurs only modest increases in net present cost of 1%, 1%, and 2%, respectively.

[2]This is only an approximation and not an exact formulation of such a policy, since we have ignored the upstream GHG emissions associated with renewable resources and battery storage manufacturing.

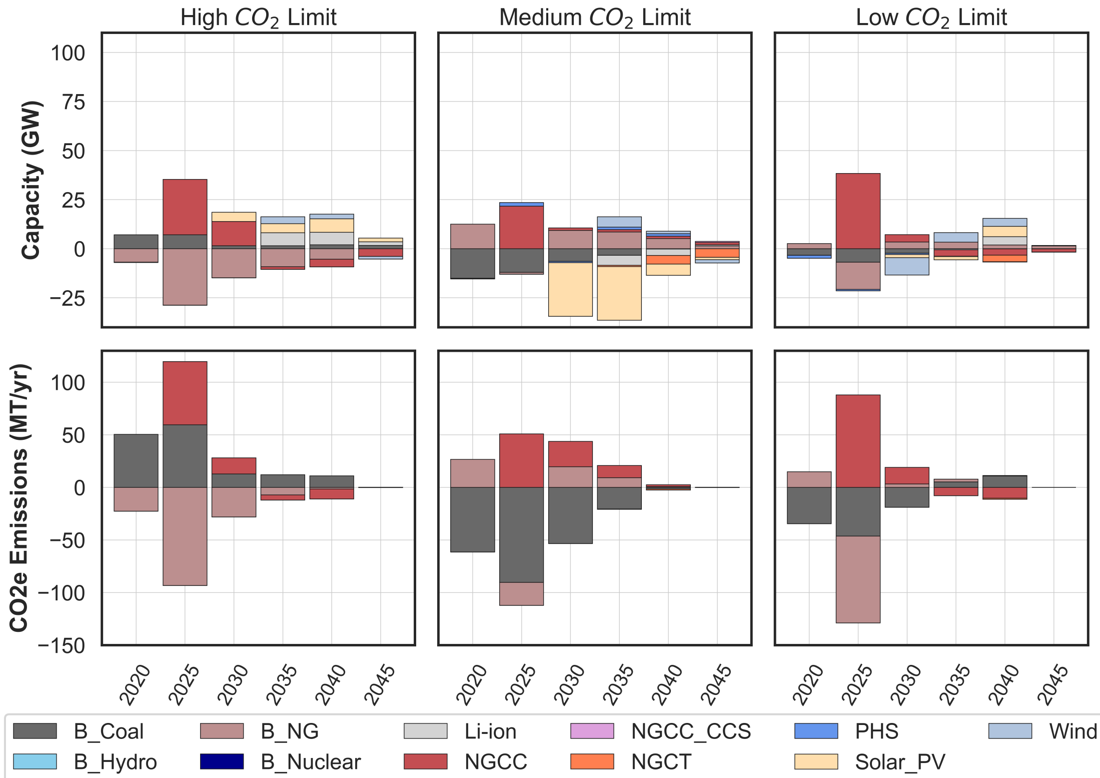

Figure 7: Accelerated Depreciation of Natural Gas – Changes in system-wide capacity (GW) and annual CO_2 emissions (MT) under the High, Medium, and Low policies with respect to the reference scenario.

3.5 Direct Regulations on New Natural Gas Deployment

We consider the impact of two regulatory measures being contemplated to avoid the potential for significant stranded costs associated with new NG power generation: 1) accelerated depreciation of NG assets without CCS that presume that there is no salvage value for these assets beyond the model planning horizon (see Section S1.2.5) and 2) a ban on new NG installations without CCS after the 2025 model period (see Section S1.2.6). Because the impact of these two regulatory measures are found to be similar, we address only the former and leave the latter to the SI (see Figure S5).

As shown in Figure 7, accelerated depreciation leads to much earlier deployment of new NG and the earlier retirement of existing NG assets compared to the reference scenario. Despite this, cumulative additions of non-CCS NG capacity are still reduced by 5-12% across the emissions policies. There were no additions of NGCT in this scenario, so all NG additions used a combined cycle design. Despite a significant change in NG deployments, accelerated depreciation affected only the stage-wise deployment of VRE, not cumulative installations by the end of the planning horizon. The solar PV and wind installations fluctuated only up to 1% in either direction regardless of emissions policy. Li-ion storage deployment was the same with the exception of a 3% increase under the High policy.

Compared to the reference scenario, the early NG deployment stimulated by accelerated depreciation regulations leads to shortened lifetimes of existing coal assets under Medium and Low policies and extended lifetimes under the High policy. In the latter case, the increased emissions budget allows for greater utilization of coal capacity in later periods, when its marginal cost of operation is lower than than both new and existing NG assets as per the assumed fuel price trajectory (see Figure S3 in the SI). Consequently, requiring accelerated depreciation of NG assets increases cumulative CO_2 emissions by 6% under the High policy but decreases emissions by 10% and 6% under the Medium and Low policies compared to respective reference cases. Interestingly, the impact of accelerated depreciation on system net present cost is relatively minor, corresponding to an increase of 0-3% across the emissions policies (see Table 2).

Sensitivity	Cost (%)			Emissions (%)		
CO_2 Policy	High	Med	Low	High	Med	Low
Reference	2.2	5.0	6.0	-31.8	-23.5	-26.9
Low Cost VRE and Storage	-2.9	-1.6	-0.4	-27.0	-24.5	-25.5
No Nuclear SLTEs	5.6	7.1	9.1	-32.6	-27.7	-33.0
Upstream Emissions	4.7	5.5	7.8	-34.1	-44.1	-40.2
Accelerated Depreciation	4.9	5.0	7.5	-27.9	-31.0	-31.2
Only CCS NG After 2025	5.3	5.6	7.2	-33.2	-29.3	-31.6

Table 2: Changes in net present cost (left) and cumulative emissions (right) with respect to the unconstrained reference scenario.

Sensitivity	Natural Gas without CCS Additions (GW)			Natural Gas with CCS Additions (GW)		
CO_2 Policy	High	Med	Low	High	Med	Low
Reference	78.8	61.9	53.6	0.0	4.3	23.4
Low Cost VRE and Storage	67.8	51.5	43.3	0.0	0.0	5.8
No Nuclear SLTEs	81.2	61.2	58.6	0.0	12.2	30.9
Upstream Emissions	69.5	59.8	48.4	0.0	0.0	6.4
Accelerated Depreciation	74.9	58.7	47.1	0.0	4.8	23.6
Only CCS NG After 2025	73.6	60.3	49.4	0.0	4.4	23.7

Table 3: Cumulative deployments of new non-CCS natural gas (left) and CCS natural gas (right).

4 Discussion

This study provides a quantitative perspective on the long-term evolution of NG resources in the transition to a deeply decarbonized power system. Under the assumption of perfect foresight, we assess how the stringency of deep decarbonization policies, as well as other technology and policy drivers, impact NG and other resource deployment and utilization, as well as overall cumulative emissions and system cost outcomes, for the U.S. Southeast. We summarize our key results below and describe their implications for utilities and regulators to consider in planning for deep decarbonization of power systems.

First, in the absence of CO_2 emissions policies, NG generation could remain a substantial part of the resource mix in the U.S. Southeast (see Figure 3). In this case, new NG capacity is installed in every stage and annual CO_2 emissions remain relatively stable throughout the model horizon, with emissions from new NG displacing those of existing thermal plants, both NG and coal. Nonetheless, the 2045 grid looks notably different than the 2020 grid as VRE and Li-ion battery storage grow from almost nothing to nearly half of system capacity, with VRE accounting for 26% of annual generation in 2045. While useful as a model benchmark, this scenario does not reflect the regional ambition and enabling policy measures to achieve deep decarbonization of the power sector by mid-century.

Second, employing CO_2 policies reduces new NG deployment by 47-71% while simultaneously reducing cumulative emissions through the planning horizon compared to the unconstrained reference case by 23-33%, with similar trends noted in the sensitivity scenarios (see Table 2). Interestingly, across the sensitivities explored here, even though new NG installations decrease monotonically with increasing policy strictness (i.e., High to Low policy), cumulative CO_2 emissions do not always follow a monotonic trend (look across rows of Table 2). Stricter 2045 emissions policies discourage near-term NG additions[3] and favor increased utilization of existing capacity beyond 2030, including both coal and existing NG power plants (see Table 4), leading to greater cumulative CO_2 emissions. In fact, in 4 out of 6 scenarios considered here (rows in Table 2), system costs and cumulative CO_2 emissions are lower under the High policy than the Low policy, which suggests that a balanced view of near-term and long-term emissions reductions would be prudent in regions with significant existing coal generation.

[3] Because the policy constraints are most binding in later model stages, they limit the operation of new NG installations more than existing thermal plants with shorter remaining lifespans.

Sensitivity	2020-2030 Coal Retirements (GW)			2020-2030 Gas Retirements (GW)		
CO_2 Policy	High	Med	Low	High	Med	Low
Reference	49.0	31.8	32.1	15.6	30.9	20.5
Low Cost VRE and Storage	41.3	32.8	29.6	17.9	16.4	26.3
No Nuclear SLTEs	48.3	39.0	41.2	19.9	18.8	17.2
Upstream Emissions	39.4	49.8	41.5	24.1	15.6	18.3
Accelerated Depreciation	41.9	43.9	38.9	44.4	31.8	34.3
Only CCS NG After 2025	47.7	40.9	39.3	41.3	51.4	43.7

Table 4: Ten-year retirements of coal (left) and natural gas (right).

Sensitivity	Solar PV Additions (GW)			Wind Additions (GW)			Li-ion Additions (GW)		
CO_2 Policy	High	Med	Low	High	Med	Low	High	Med	Low
Reference	202.4	227.5	248.8	143.0	156.7	159.9	71.7	89.7	102.3
Low Cost VRE and Storage	215.6	247.6	281.5	132.8	151.1	171.0	89.1	107.1	118.0
No Nuclear SLTEs	250.8	258.6	278.4	179.6	189.9	210.5	89.5	98.1	111.7
Upstream Emissions	220.8	238.6	276.0	150.1	179.6	161.6	84.8	92.4	117.5
Accelerated Depreciation	204.3	226.3	248.7	141.6	155.1	160.0	73.5	90.3	102.2
Only CCS NG After 2025	207.8	227.9	248.2	138.3	156.3	160.1	77.5	89.4	102.4

Table 5: Cumulative deployments of solar PV (left), wind (center), and Li-ion discharge capacity (right).

Third, all else remaining equal, we find that policies discouraging new NG deployment, such as accelerated depreciation and no new gas without CCS after 2025, generally lead to greater cumulative emissions reductions compared to the reference scenario (i.e., the cases without these policies but all else remaining equal) along with marginal increases in systems costs (e.g., 1-3% higher in system cost as shown in Table 2). We find that such policies make it attractive to support early build out of NG generation to displace coal generation in the near term, while at the same time limiting cumulative NG deployment in a way that minimizes asset stranding in later periods when emissions constraints are increasingly stringent. At the same time, it should be noted that new NG may operate differently in a low-carbon power system. As shown in Figure S6, we observe steep declines in NG capacity factors over time across scenarios. This suggests a changing role for NG plants focused primarily towards contributing to system reliability by providing power due to periods of high net load (i.e., load minus VRE generation).

Fourth, not granting SLTEs for nuclear power plants result in the highest cost outcomes, but because nuclear capacity is phased out in later model periods when carbon emissions are most constrained, the cumulative emissions impacts are estimated to be relatively small. In this case, the absence of nuclear capacity is made up for by other low-carbon generation in the form of wind, solar PV, Li-ion storage, and NGCC-CCS. If nuclear capacity were to be retired in the near-term without long-term policy directive on power system emissions trajectory, the retired capacity could be replaced with either increased use of emissions-heavy coal generation or new thermal capacity as opposed to zero- or low-carbon technologies.

Fifth, nearly all of the scenarios under the Low policy include the late deployment of NGCC-CCS as a means of dispatchable, low-carbon generation, a result that existing literature has shown to be influential in reducing the cost of deep decarbonization of power systems.[7] An important caveat is the need to reduce upstream emissions associated with the NG supply chain below currently estimated levels. Specifically, our analysis suggests that if current estimates of upstream emissions are maintained and accounted for in power sector CO_2 emissions limits, it will not only discourage near-term NG deployment, but also discourage NGCC-CCS deployment even under the most stringent emissions policies (i.e., the Low policy).

Overall, the specific system impacts of the sensitivity factors described in Table 1 (i.e, Low VRE and Storage Costs, No Nuclear SLTEs, etc.) are more varied and subtle than those resulting from deep decarbonization emissions policies (i.e., the High, Medium, Low policies). Importantly, utilities and regulators should take confidence from the fact that a broad distribution of key uncertainties results in only marginal differences in expected net present costs of decarbonization, cumulative emissions, and even system capacity (see Table 2). This suggests that there are many possible pathways for deep decarbonization with similar cost and cumulative emissions outcomes, all of which emphasize rapidly expanding VRE deployment in the near-term and displacing coal generation.

Future research should seek to address limitations from this work which notably relate to our least-cost modeling framework as well as our representation of new and existing generating technologies.

While this analysis utilizes an advanced, multi-period capacity expansion model, key limitations include: (1) an assumption of perfect foresight over the entire planning horizon, which does not reflect the practical reality of long-term cost and policy uncertainty facing grid planners and regulators; (2) disregarding operating or planning reserve requirements, a consideration which many states require in integrated resource planning processes, and which could incentivize deployment of balancing resources like battery storage as well as additional NG plants as peaker resources; and (3) ignoring certain upstream and downstream costs of new capacity, such as additional NG infrastructure costs. Some of these new considerations, such as reserves requirements, are possible within the existing framework but were foregone for the sake of computational efficiency. The adequate representation of uncertainty in long-term drivers of system evolution, namely, policy uncertainty, technology cost uncertainty and demand uncertainty, can be formulated as part of a multi-stage stochastic programming framework, but these approaches are limited in the number of discrete scenarios that can be considered and often need specialized solution algorithms.[37] Methodological advances to improve the scalability of multi-stage stochastic programming CEM formulations are thus an important area of future work. The implications of NG deployment in the power sector on gas infrastructure can be studied by expanding the planning problem to consider gas-electric interactions as has been proposed by other recent studies.[38][39] In addition, given the many possible decarbonization pathways with similar cost outcomes, a multi-criteria analysis that evaluates these scenarios on other metrics of interest (e.g., employment effects, distributional impacts, local air pollution related health impacts) could be valuable to narrow down the list of scenarios to be prioritized.

Achieving the resource portfolios selected across the scenarios considered would require an unprecedented scale and speed of new investments. As noted above, the 2035 annual average deployment rates of solar PV and wind are about comparable or larger than the 2019 *nationwide* annual deployment rates. Moreover, installations increase dramatically beyond this rate for both solar PV and wind beginning in 2040, the first model period where the installation limit constraints are removed. For example, the annual rate of solar PV and wind capacity additions are 1.7x and 1.5x greater, respectively, than their 2035 instillation rates in the High policy reference case. The results from scenarios evaluating direct regulations on new NG deployment suggest a similarly unprecedented buildout, except in the near-term. For example, 52 GW of new gas capacity is built between 2025 and 2030 in the High accelerated depreciation case. By comparison, about 35 GW of new NG capacity is currently planned nationwide between 2021 and 2025.[29] It must be emphasized that our modeling results not be interpreted as *predictive* of investment, operational, or emissions outcomes under the technology and policy pathways evaluated; rather, results should *inform* evaluation of the risks and opportunities of various emissions reductions pathways.

With regard to emerging technologies, our model does not consider promising options including long-duration energy storage, advanced nuclear technologies, and hydrogen-fired power plants.[9][10][7] Additionally, our analysis is limited to supply-side resources: we do not consider the effects of demand-side energy management or energy efficiency on resource planning outcomes even when these options may become much more flexible and available in a highly electrified future. This is particularly notable given that results show NG operating at low capacity factors in later model stages, indicating that much of the value of NG in a decarbonized system lies in providing the same sort of reliability that can potentially be offered by a combination of demand-side resources. Finally, we do not consider the possibility of retrofitting existing power generation resources to shift them to serve as low-carbon generation or storage. Existing coal-fired power plants have already been retrofit with CCS technology in the United States and Canada, and retrofitting existing NGCC plants is technically feasible.[40] Recently announced partnerships to explore molten-salt thermal storage retrofits of an existing coal plant are another possibility.[41] Furthermore, major turbine manufactures are developing the technology to allow for high-volume hydrogen firing of NGCC turbines, aiming to demonstrate 100% hydrogen firing in the coming years.[42] The ability to model retrofits of new or existing resources for CCS, molten-salt thermal storage, or hydrogen co-firing could present a more accurate representation of how the grid may evolve in practice.

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Supplemental Information

S1 Methods

S1.1 Capacity Expansion Modeling

For this analysis, we used GenX – an open-source, high resolution, least-cost capacity expansion model – as described in the online documentation.[17] GenX has traditionally been used to model a single year of grid operations, including a single investment stage. However, planning for future grids with high levels of variable renewable energy (VRE) and evolving carbon policies requires detailed modeling of grid operations over multiple planning stages. A multi-stage model also allowed us to incorporate dynamic cost information and lifetime retirements for new and existing capacity. We employed the well-known dual dynamic programming (DDP) algorithm – as described in Lara et al. (2018) – to adapt GenX to a multi-stage planning environment with perfect foresight.[25]

We configured the GenX model with six, five-year planning stages spanning from 2020 to 2045. Beginning with the 2025 model period, investment cost assumptions and fixed O&M (FOM) cost assumptions from 5 years prior were used, to capture the fact that project financing typically occurs years before plants become operational. Additionally, we configured GenX to model unit commitment of thermal power plants under a linear relaxation assumption, which has been shown to be a reasonable approximation when considering capacity expansion under decarbonization constraints.[23] Network expansion of existing transmission was also enabled. However, operating reserves were not modeled due to the substantial increase in memory and computational time that this would require. Only retirements, not investments in new capacity, were allowed during the first planning stage; retirements and capacity additions were allowed in all subsequent planning periods.

S1.2 Model Scenarios

S1.2.1 Carbon Emissions Reduction Policies

We consider the effects of three emissions reduction policies – High, Medium, and Low – with increasingly stringent limits on annual CO_2 emissions, in addition to a fourth, "no emissions policy" case used only in the reference scenario. All emissions reductions policies were computed relative to a 2007 baseline level of CO_2 emissions, the maximum emissions year for the U.S. Southeast. Using 2019 U.S. Energy Information Agency (EIA) state-level summary tables, this baseline was computed as approximately 500 million tonnes (MT) of CO_2 per year over the entire model region and was used as the 2020 emissions cap.[43] All three policies require emissions reductions of 50% by 2030 compared to this baseline, or a model region-wide annual emissions limit of 250 MT CO_2 (see Table S1). In 2045, the High policy requires a 90% emissions reduction (50 MT annual CO_2 limit), the Medium policy a 95% reduction (25 MT annual CO_2 limit), and the Low policy a 99% reduction compared to this baseline. These three policies were chosen to represent various mid-century emissions targets that a deep decarbonization strategy may aim for, with varying levels of expected emissions offsets.

In addition to the limits imposed in the 2020, 2030, and 2045 model periods, emissions caps were imposed on interim stages. These limits were computed via linear interpolation of emissions caps from 2020 to 2030 and from 2030 to 2045. This resulted in an annual emissions limit of 375 MT in 2025 under all three policies, and policy-dependent limits for 2035 and 2040.

	Annual CO_2 Emissions (MT)					
CO_2 Policy	**2020**	**2025**	**2030**	**2035**	**2040**	**2045**
High CO_2 Limit	500	375	250	183	117	50
Medium CO_2 Limit	500	375	250	175	100	25
Low CO_2 Limit	500	375	250	168	87	5

Table S1: Annual model region-wide CO_2 emissions limits (MT) by emissions reduction policy.

S1.2.2 Low VRE and Storage Costs

We evaluate "moderate" and "advanced" technological advancement trajectories for solar PV, wind, and battery storage as specified in the National Renewable Energy Laboratory's (NREL) 2020 Annual Technology Baseline (ATB) where "moderate" represents mid-level future cost projections and "advanced" represents low-level future cost projections.[27] Though capital costs and FOM costs decline, variable O&M (VOM) costs do not change for any technologies between the two forecasts. The "advanced" and "moderate" ATB scenarios correspond to the "low" and "medium" (i.e., "baseline") VRE cost scenarios, respectively.

S1.2.3 Second Lifetime Extensions for Existing Nuclear Plants

Our default assumption is that all existing nuclear plants in the Southeast receive a second lifetime extension (SLTE), which would lead to an 80-year assumed operational lifetime for existing nuclear capacity. Under this assumption, there would be no retirements in the existing nuclear fleet before 2050. We assume that there are no re-licensing or refurbishing costs associated with SLTEs, and plants continue to operate under the same cost and performance assumptions.

We test the impact of nuclear SLTEs by including a scenario where none are granted. This results in a 60-year operational lifetime assumption for all existing nuclear power plants in the Southeast, and for assumed operational capacity to decline from 32.9 GW in the 2020 model period to 23.6 GW, 18.6 GW, and 9.5 GW in the 2035, 2040, and 2045 model stages, respectively.[29]

S1.2.4 Upstream GHG Emissions for Coal and Natural Gas

Our default assumption is that power sector-focused carbon policies only consider combustion-level CO_2 emissions. As a sensitivity, we consider the impact of including upstream, non-combustion emissions rates for natural gas (NG) and coal assets in these policies by using the supplemented emissions rates, in Table S2, taken from the Argonne National Laboratory GREET Model.[44]. Here, non-CO_2

greenhouse gasses (GHG) like methane and N_2O are converted to CO_2-equivalents (CO_2eq) using their 100-year global warming potential (GWP), where the GWP of methane is 30 CO_2eq and the GWP for N_2O is 265 CO_2eq.

Fuel Type	**CO_2 Content (tons/MMBtu)** Combustion Only	Combustion + Upstream
Uranium	0	0
Coal	0.0953	0.1014
Natural Gas	0.0531	0.0662
Natural Gas w/ CCS	0.0053	0.0184

Table S2: CO_2 content of fuel sources. (Sources: EIA, 2021;[45] Argonne National Laboratory, 2021.[44])

S1.2.5 Salvage Value for Natural Gas Without CCS After 2050

We explore the effect of financial assumptions related to the salvage value of new natural gas combustion turbine (NGCT) and natural gas combined cycle (NGCC) power plants without carbon capture and storage (CCS). We consider two financial models – one which assumes that undepreciated costs of these plants after the model horizon are fully recoverable, and a second which requires that all capital costs be paid in full before the end of the model horizon. We refer to the first as the "rental" financial model, and the second as the "full-cost" financial model.

In the **rental financial model**, annualized investment costs are modeled as rental payments for each year's use of a capital asset. We only pay for the years in which the capital asset is able to be used – i.e., the model does not consider annualized investment costs which would occur after the model horizon. The annualized investment cost AIC of an asset in period p with weighted annual cost of capital $WACC$ and overnight capital cost $C^{overnight}$ is computed using the following formula:

$$AIC_p = \frac{WACC \cdot C^{overnight}}{1 - (1 + WACC)^{-L}}$$

where L is the economic lifetime of the asset. The adjusted total capital cost under the "rental" financial model, C^{rental}, the discounted sum of the annual "rents" paid within the model horizon, is computed as follows:

$$C_p^{rental} = \sum_{i=1}^{min(L,Y_p)} \frac{AIC_p}{(1 + WACC)^i}$$

where Y_p is the number of years remaining between the start of period 0 and the end of the planning horizon for resource type p. Note that when $L \leq Y_p$, $C_p^{rental} = C^{overnight}$; that is, the sum of rental payments is equal to the overnight capital cost. When $L > Y_p$, however, $C_p^{rental} < C^{overnight}$; that is, the sum of rental payments is less than the overnight capital cost.

For example, suppose we build a capital asset in 2030 with an overnight capital cost of \$1,000,000 and an economic lifetime of 30 years. With a $WACC$ of 4.5%, this translates to an annualized investment cost of about \$67,000. However, if the model horizon only extends through 2050, we would only pay this amount annually for 20 years, not the full 30 years of the asset's economic life. This means that from the model's perspective, the adjusted total capital cost equals the discounted sum of these rents over this 20-year period, which is about \$800,000.

In the **full-cost financial model**, we assume that there is no salvage value for NG assets without CCS beyond the model horizon. After 2050, they become "stranded assets" without any useful economic value. Therefore, the full-cost financial model requires that all capital costs of new NG plants without CCS be paid in full within the model horizon. This means that $C_p^{full-cost} = C^{overnight}$ for all stages.

S1.2.6 CCS Requirement for New Natural Gas Beginning in 2030

We consider the effect of requiring all deployment of new NG capacity beginning in 2030 to include CCS. This constraint implies that NG power plants without CCS may only be built in the 2025 model stage.

S1.2.7 Reference Scenario

A reference scenario is established as a baseline against which to compare how the sensitivities described above impact relative costs, emissions, and capacity mixes. The reference scenario includes a case for each CO_2 policy and the unconstrained "no emissions policy" case, uses "moderate" technology advancement assumptions (i.e., baseline costs for VREs and battery storage), assumes that SLTEs are granted for all existing nuclear power plants (i.e., all existing nuclear capacity remains online through the final 2045 model period), considers only combustion-level emissions (i.e., does not include the CO_2 equivalent of fugitive methane and N_2O emissions), assumes full salvage value for all resources post-planning horizon (i.e., "rental" financial model for all assets), and after the first model period, imposes no constraints on when new NG capacity may be deployed (i.e., new NG capacity may be built any model period beyond the first, where no new investments of any kind are allowed).

S1.3 Data

Four model regions from the United States Environmental Protection Agency's (EPA) Power Sector Modeling Platform v6 (IPM model) – S_C_TVA, S_VACA, S_SOU, and FRCC – were used to define the boundaries of the Southeast model (see Figure 2).[28] These four model regions include parts of the seven Southeastern states outside of wholesale power markets.

The Southeast model is configured to represent 17 unique generating technologies in each model region listed in Table S3. Seven of these resource types exclusively represent existing, or "brownfield" capacity, and are not eligible for new capacity additions but may be retired due to lifetime or economic considerations. Brownfield thermal resource types not eligible for new capacity additions include existing NGCC plants, existing NGCT plants, existing natural gas steam turbine (NGST) plants, existing conventional steam coal plants, and existing nuclear plants. Brownfield hydroelectric resources not eligible for new capacity additions include run-of-river hydroelectric plants and reservoir hydroelectric plants. Other resource types are used to exclusively represent new, or "greenfield," capacity additions. These resources include new NGCC plants, new NGCC plants with CCS (NGCC-CCS), new NGCT plants, new nuclear plants, and new utility-scale Li-ion battery storage facilities (Li-ion). Finally, some resource types are used to represent both existing capacity and new capacity additions. These include utility-scale solar photovoltaic facilities (solar PV), pumped hydroelectric storage facilities (PHS), and onshore wind turbine (wind) facilities. The wind resource type is broken down into three sub-types in each model region, representing the different qualities of developable sites in that region by wind availability and grid interconnection costs, as per Brown and Botterud (2021).[33]

Resource Name	Label	Includes Brownfield Capacity?	Eligible for Capacity Expansion?
Conventional Steam Coal	B_Coal	Yes	No
Reservoir Hydroelectric	B_Hydro	Yes	No
Run-of-River Hydroelectric	B_Hydro	Yes	No
Natural Gas Combined Cycle (Existing)	B_NG	Yes	No
Natural Gas Combustion Turbine (Existing)	B_NG	Yes	No
Natural Gas Steam Turbine (Existing)	B_NG	Yes	No
Nuclear (Existing)	B_Nuclear	Yes	No
Pumped Hydroelectric Storage	PHS	Yes	Yes
Solar Photovoltaic	Solar_PV	Yes	Yes
Onshore Wind Turbine (1)	Wind	Yes	Yes
Onshore Wind Turbine (2)	Wind	Yes	Yes
Onshore Wind Turbine (3)	Wind	Yes	Yes
Li-ion Battery Storage	Li-ion	No	Yes
Natural Gas Combined Cycle	NGCC	No	Yes
Natural Gas Combined Cycle with CCS	NGCC_CCS	No	Yes
Natural Gas Combustion Turbine	NGCT	No	Yes
Nuclear	Nuclear	No	Yes

Table S3: List of resources included in the Southeast model, including whether each resource type includes representations of brownfield capacity and whether it is eligible for capacity additions.

S1.3.1 Brownfield Capacity

The 2018 Form EIA-860 was used to compute total existing capacity of brownfield resource types in each region (see Figure 2 and Table S4). We include the following subset of technologies from the EIA-860 form: "Solar Photovoltaic," "Onshore Wind Turbine," "Nuclear," "Natural Gas Steam Turbine," "Natural Gas Fired Combined Cycle," "Natural Gas Fired Combustion Turbine," "Conventional Steam Coal," "Conventional Hydroelectric," and "Hydroelectric Pumped Storage".[29] We subdivided "Conventional Hydroelectric" into two subsets – "Run-of-River Hydroelectric" and "Reservoir Hydroelectric" – based on individual plant classifications from the 2019 Oak Ridge National Laboratory Existing Hydropower Assets Plant Data Set.[46] Additionally, values for existing nuclear capacity in the S_SOU region as computed from the EIA-860 data were augmented by 2.50 GW, the combined capacities of the Vogtle 3 and 4 units under construction in Georgia, expected to be completed in 2023. Although Form EIA-860 includes several additional resource types that contribute to existing capacity, this selection accounts for 95% of existing capacity across the four model regions.[29]

	S_C_TVA	S_VACA	S_SOU	FRCC
Conventional Steam Coal	7,150	16,746	19,000	7,307
Reservoir Hydroelectric	2,735	834	2,939	0
Run-of-River Hydroelectric	1,537	1,623	1,144	12
Natural Gas Combined Cycle	9,924	9,363	19,846	32,343
Natural Gas Combustion Turbine	5,268	10,904	12,398	9,000
Natural Gas Steam Turbine	63	589	4,064	2,543
Nuclear	8,475	12,270	8,318	3,797
Pumped Hydroelectric Storage	1,809	2,657	1,635	0
Solar Photovoltaic	293	3,584	1,239	1,282
Onshore Wind Turbine	29	0	0	0

Table S4: Brownfield capacity (MW) by region for each of the technology types. (Source: EIA-860.[29])

The PowerGenome data aggregation software was used to obtain the FOM costs, VOM costs, average heat rates, and minimum power outputs for existing thermal power plants in each of the four model regions.[30] These parameters are summarized in Table S6.

Economic and operational characteristics of existing nuclear power plants are taken from Sepulveda et al. (2018).[7] Unlike those of existing fossil fuel-fired power plants, the operational characteristics of existing nuclear power plants are assumed to be identical across all model regions. These parameters are summarized in Table S6.

To model unit commitment of thermal resources, GenX requires parameters characterizing start-up costs, start-up fuel requirements, ramp-up and ramp-down rates, minimum up-times, and minimum down-times. Taken from Sepulveda et al. (2018), PowerGenome, Kumar et al. (2012), and UT Austin (2018), these unit commitment parameters for existing thermal resources, which are identical across model regions and all model periods, are summarized in Table S5.[7]

Brownfield Resource	**Start Cost (\$/MW/ start)**	**Start Fuel (MMBtu/ MW/start)**	**Ramp Up**	**Ramp Down**	**Up Time (Hrs.)**	**Down Time (Hrs.)**
NGCC	79	9.00	100%	100%	1	1
NGCT	52	0.22	100%	100%	4	4
NGST	75	9.00	16%	16%	12	12
Coal	120	13.70	57%	57%	24	24
Nuclear	1,000	0.00	25%	25%	36	36

Table S5: Unit commitment operational parameters for brownfield resources (Sources: PowerGenome;[30] Sepulveda et al. (2018);[7] Kumar et al. (2012);[47] and UT Austin (2018).[48])

Like existing nuclear capacity, existing reservoir, run-of-river, and pumped storage hydroelectric facilities are assumed to have the same cost and operating characteristics across model regions. FOM and VOM costs for run-of-river and reservoir hydropower were taken from the 2018 NREL ATB's "Powering Non-Powered Dams" (NPD) hydropower resource type under "moderate" technology advancement assumptions.[31] FOM costs for PHS were taken from the MIT Future of Storage Study (while VOM costs are specified as \$0/MWh in the MIT Future of Storage study, we apply a marginal \$1/MWh cost to disincentivize excessive cycling in our model).[32] These are summarized in Table S6.

Each technology was assigned an operational lifetime equal to its economic lifetime, which was used to compute annual investment costs. Plant retirement data from the EPA's eGRID2019 data set was used to compute capacity-weighted average lifetimes of fossil fuel-fired power plants.[49] Lifetimes for new and existing NGCC, NGCT, and NGST power plants were computed based on nationwide

Region	FOM Cost ($/MW-yr)	VOM Cost ($/MWh)	Heat Rate (MMBtu/MWh)	Minimum Power Output
		Existing Natural Gas Fired Combined Cycle		
S_C_TVA	10,019	3.50	6.92	37%
S_VACA	10,641	3.56	7.27	42%
S_SOU	11,606	3.58	7.27	53%
FRCC	12,078	3.58	7.35	70%
		Existing Natural Gas Fired Combustion Turbine		
S_C_TVA	7,326	11.30	14.75	46%
S_VACA	7,477	11.30	12.17	54%
S_SOU	7,546	11.30	11.84	58%
FRCC	7,697	11.30	12.92*	45%
		Existing Natural Gas Fired Steam Turbine		
S_C_TVA	17,798	7.35	10.35	40%
S_VACA	49,776	1.00	11.55	28%
S_SOU	30,518	1.00	11.58	34%
FRCC	29,173	1.00	11.17	15%
		Existing Conventional Steam Coal		
S_C_TVA	60,901	1.80	10.93	45%
S_VACA	59,806	1.80	10.18	34%
S_SOU	59,412	1.80	10.32	49%
FRCC	58,567	1.80	10.65	38%
		Existing Nuclear		
All	118,988	2.32	10.46	50%
		Existing Reservoir Hydroelectric		
All	14,000	0.02	–	10%
		Existing Run-of-River Hydroelectric		
All	14,000	0.02	–	0%
		Existing Pumped Hydroelectric Storage		
Region	**FOM Cost ($/MW-yr)**	**VOM Cost ($/MWh)**	**Charging Efficiency**	**Discharge Efficiency**
All	41,000	1.00	89%	89%

Table S6: Economic and operational parameters for brownfield natural gas, coal, nuclear, and hydroelectric resource types. The value marked with an asterisk (*) represents a manually adjusted data field; to address a data anomaly in the PowerGenome data in the average heat rate of existing natural gas-fired steam turbines in the Florida model region, the original value was replaced by the average of heat rates from the other three model regions. (Sources: PowerGenome;[30] Sepulveda et al. (2018);[7] 2018 NREL ATB;[31] and the MIT Future of Storage Study.[32])

capacity-weighted averages of plant retirement ages whereas lifetimes for existing coal plants approximate the capacity-weighted average retirement age of coal plants within each Southeast model region using data from the closest approximate eGrid region ("SRTV" eGrid region corresponding to S_C_TVA, "SRVC" corresponding to the S_VACA, "SRSO" corresponding to S_SOU, and "FRCC" corresponding to FRCC). Nuclear power plants are assumed to have either a 60- or 80-year operational life, based on whether we assume that existing nuclear plants receive SLTEs. See Table S7 for operational lifetimes of all resources across model regions. Using these region- and resource-specific lifetimes, expected lifetime retirements were computed for existing capacity of each resource type for each model stage. For each existing generating facility, we added its assumed operational lifetime to the year the facility began operation (as specified by the "Operating Year" field in Form EIA-860) to obtain the year we expect that facility to retire.[29] We require the model to retire that facility at the start of the first model stage whose year exceeds or equals the expected retirement year.

	Lifetime (years)			
Resource	**S_C_TVA**	**S_VACA**	**S_SOU**	**FRCC**
Conventional Steam Coal	59	54	51	40
Pumped Hydroelectric Storage	50	50	50	50
Natural Gas Combined Cycle	27	27	27	27
Natural Gas Combustion Turbine	44	44	44	44
Natural Gas Steam Turbine	55	55	55	55
Nuclear	60/80	60/80	60/80	60/80
Onshore Wind Turbine	30	30	30	30
Reservoir Hydroelectric	100	100	100	100
Run-of-River Hydroelectric	100	100	100	100
Solar Photovoltaic	30	30	30	30
Li-ion Battery Storage	15	15	15	15
Natural Gas Combined Cycle with CCS	30	30	30	30

Table S7: Operational and economic lifetime assumptions for resources in the Southeast model. Note that nuclear resource lifetimes are assumed at either 60 or 80 years depending on whether SLTEs are granted. (Sources: 2020 NREL ATB;[27] and EPA eGrid2019.[49])

S1.3.2 Greenfield Capacity

The 2020 NREL ATB was used to obtain economic and operational characteristics of new natural gas-fired power plants (NGCC, NGCT, and NGCC-CCS), nuclear power plants, utility-scale solar PV, onshore wind, and Li-ion storage.[27] We supplemented these parameters with additional data sources noted below. We assume a 30-year capital recovery period (CRP) and "Market Factor" financial parameters for all these technologies with the only exception of Li-ion battery storage, which uses a 20-year CRP. For all technologies, we assume an after-tax weighted average cost of capital (WACC) of 4.5%. See Table S20 for a summary of key model parameters and assumptions.

For the three greenfield NG technologies, we used the "AverageCF" capacity factor rating.[27] Table S8, Table S9, and Figure S1 summarize the cost and operational parameters for new thermal power plants in 2020, overnight investment cost projections for new thermal power plants through 2045, and additional technical characteristics of thermal power plants required for modeling unit commitment.

For VRE technologies, we referred to the 2020 NREL ATB for investment costs and FOM costs.[27] "Class 5" assumptions were used for wind resources. Although the 2020 ATB specifies a \$0/MWh VOM cost for onshore wind, we set this value to \$.01/MWh to ensure that solar PV is dispatched first by the model. Model region-specific interconnection costs (added to the ATB overnight investment costs), average capacity factors, and maximum developable capacity were generated via the software tools introduced in Brown and Botterud (2020).[33] Lastly, solar PV and wind resources were subject to maximum single-stage installation limits for the 2025, 2030, and 2035 model stages, derived from the 2030 "Step 1" capacity limit used in the EPA IPM model as specified in Table 4-14 in "2020 Update" documentation.[28] A single installation limit was applied to the three wind resource bins in aggregate. These nationwide annual capacity limits were scaled down proportional to the share of 2019 U.S.-wide

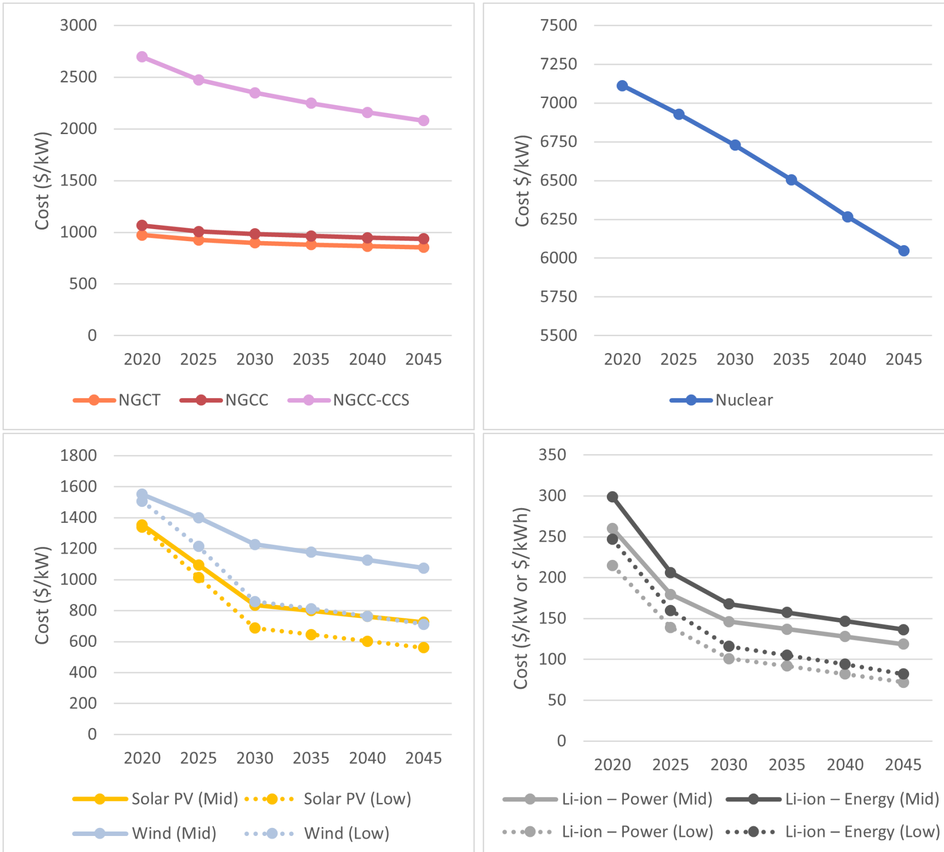

Figure S1: Overnight investment cost projections ($/kW or $/kWh) for new natural gas, nuclear, VRE, an Li-ion capacity. (Source: 2020 NREL ATB.[27])

annual generation attributed to the Southeast model regions and multiplied by 5 to reflect the 5-year duration of each stage. Tables S10, S11, S12, S13, and S14 as well as Figure S1 summarize these assumptions.

For Li-ion battery storage, we supplemented 2020 NREL ATB with another NREL report's cost projections for utility-scale battery storage.[27][50] Note that costs for discharging power (MW) and energy capacity (MWh) are considered separately in the model, which allows it to optimize the duration of storage discharged at rated power within a specified range. These cost and operational assumptions are summarized in Table S15 and Figure S1.

Pumped hydroelectric storage supply curves from the 2018 Hydropower Vision study at the Regional Energy System Deployment (ReEDs) model balancing area (BA) level were used to estimate capital costs and maximum capacity limits for new facilities.[34][35] ReEDs BAs were aggregated to approximate the PHS storage potential within each of the four Southeast model regions. Where the ReEDs BA intersected only a portion of an IPM region, the resource potential was scaled down proportional to the intersected area. The supply curve data suggests that there is potential for new PHS investment only in the S_SOU and S_C_TVA model regions even though Form EIA-860 indicates that there is existing PHS capacity in the S_VACA model region.[29] For each ReEDs BA, four bins were provided which represent PHS sites at different costs per MWh. We limit new allowable PHS capacity to that of the lowest-cost bin in each respective region and only allow new PHS capacity to be built in the S_SOU and S_C_TVA regions. Costs, maximum new capacity, and additional technical assumptions are summarized in Tables S6 and S16.

Resource	**FOM ($/MW-year)**	**VOM ($/MWh)**	**Start Cost ($/MW/ start)**	**Start Fuel (MMBtu/ MW/start)**
NGCT	11,395	4.50	140	0.19
NGCC	12,863	2.16	61	0.20
NGCC–CCS	26,994	5.72	97	0.20
Nuclear	118,988	2.32	1,000	0.00

Table S8: Cost parameter assumptions for new thermal power plants for the 2020 model stage. (Sources: 2020 NREL ATB;[27] and Kumar et al. (2021).[47])

Resource	**Capacity Size (MW)**	**Heat Rate (MMBtu /MWh)**	**Ramp Up**	**Ramp Down**	**Up Time (Hrs.)**	**Down Time (Hrs.)**	**Minimum Stable Output**
NGCT	237	9.51	100%	100%	0	0	25%
NGCC	573	6.40	100%	100%	4	4	30%
NGCC-CCS	377	7.12	100%	100%	4	4	50%
Nuclear	1,000	10.46	100%	100%	36	36	20%

Table S9: Operational parameter assumptions for new thermal power plants. (Sources: Sepulveda et al. (2020);[7] 2020 NREL ATB;[27] EIA-860;[29] Mallapragada et al. (2020);[36] Kumar et al. (2021);[47] EIA Annual Energy Outlook Electric Market Module;[51] Jenkins et al. (2018);[52] Oates et al. (2014);[53] and GE 7HA Fact Sheet.[54])

Resource	Technology Advancement Assumption	Overnight Investment Cost ($/MW)	FOM ($/MW-year)	VOM ($/MWh)
Solar_PV	Advanced	1,340,034	15,694	0
	Moderate	1,353,543	15,852	0
Wind	Advanced	1,556,755	41,734	0.01
	Moderate	1,578,350	42,496	0.01

Table S10: Cost and operational parameter assumptions for solar PV and wind resources for the 2020 model period. (Source: 2020 NREL ATB.[27])

	Interconnection Cost Adder ($/MW)			
Region	**Solar_PV**	**Wind (1)**	**Wind (2)**	**Wind (3)**
S_C_TVA	74,563	114,464	157,338	102,886
S_VACA	43,015	68,955	70,192	66,547
S_SOU	53,837	78,887	114,347	130,954
FRCC	30,200	37,898	68,386	93,796

Table S11: Interconnections cost adders ($/MW) for solar PV and wind resources. (Source: Computed via software tools introduced in Brown and Botterud (2020).[33])

	Maximum Capacity Limits (MW)			
Region	**Solar_PV**	**Wind (1)**	**Wind (2)**	**Wind (3)**
S_C_TVA	2,420,648	179,342	96,299	23,181
S_VACA	2,035,425	157,135	73,001	11,349
S_SOU	2,758,571	155,550	190,210	54,325
FRCC	933,392	18,245	73,346	31,618

Table S12: Maximum capacity limits (MW) for solar PV and wind resources. (Source: Computed via software tools introduced in Brown and Botterud (2020).[33])

	Stage-Level Maximum Installation Limits (MW)					
	Stage 1	**Stage 2**	**Stage 3**	**Stage 4**	**Stage 5**	**Stage 6**
Solar_PV	N/A	48,053	48,053	48,053	None	None
Wind	N/A	78,941	78,941	78,941	None	None

Table S13: Maximum installation limits (MW/stage) for solar PV and wind resources. "N/A" is specified in Stage 1 because no capacity additions of any kind are allowed. (Source: EPA IPM model.[28])

	Average Capacity Factors (%)			
Region	**Solar_PV**	**Wind (1)**	**Wind (2)**	**Wind (3)**
S_C_TVA	24%	37%	31%	21%
S_VACA	25%	37%	29%	20%
S_SOU	26%	35%	32%	28%
FRCC	27%	33%	31%	29%

Table S14: Average capacity factors (%) of solar PV and wind resources. (Source: Hourly capacity factor profiles computed via software tools introduced in Brown and Botterud (2020).[33])

Lithium-ion Battery Storage (Li-ion)		
Technology Advancement	**Advanced**	**Moderate**
Overnight Discharge Investment Cost ($/MW)	214,966	260,021
Overnight Energy Investment Cost ($/MWh)	246,899	298,647
FOM Discharging Cost ($/MW-yr)	250	750
FOM Energy Cost ($/MW-yr)	1,420	2,230
VOM Cost ($/MWh)	1.00	1.00
Charging Efficiency	92%	92%
Discharging Efficiency	92%	92%
Minimum Duration (Hrs.)	0.25	0.25
Maximum Duration (Hrs.)	200	200
Self-Discharge (Fraction/Hr.)	0.002	0.002

Table S15: Cost and operational parameter assumptions for Li-ion battery storage in the 2020 model period. Note that while VOM costs are specified as $0/MWh in the NREL ATB, we apply a marginal $1/MWh cost to disincentivize excessive cycling in our model. (Source: NREL ATB 2020;[27][50] and the MIT Future of Storage Study.[32])

Pumped Hydroelectric Storage (PHS)		
Region	**Maximum Capacity (MW)**	**Overnight Investment Cost ($/MW)**
S_C_TVA	4,450	1,509,439
S_SOU	2,535	1,894,728

Table S16: Investment costs ($/MW) and maximum capacity limits (MW) for PHS. (Source: Analysis of 2018 Hydropower Vision study PHS supply curves.[34])

S1.3.3 Fuel Costs

The 2020 EIA Annual Energy Outlook (AEO) Reference Case was used for the fuel costs associated with NG, coal, and nuclear power plants. "Electric Power" fuel costs in $/MMBtu for "natural gas," "steam coal," and "uranium," were used for each of these resource types, respectively.[55] Additional EIA data were used to establish CO_2 content for each fuel type.[56] As coal-fired power plants in the Southeast use coal from both the western and eastern United States, we used the average of CO_2 emissions per MMBtu of bituminous and subbituminous coal to approximate the emissions rates from these facilities.[57] NGCC-CCS plants were assumed to have a 90% CO_2 capture rate, and a capture and sequestration cost of $20/tonne CO_2. Fuel CO_2 content and costs are summarized in Tables S2 and S17.

	Fuel Cost ($/MMBtu)					
Fuel Type	**2020**	**2025**	**2030**	**2035**	**2040**	**2045**
Uranium	0.67	0.68	0.69	0.70	0.71	0.72
Coal	2.05	1.94	1.94	1.94	1.94	1.94
Natural Gas	2.64	3.29	3.61	3.72	3.78	3.83
Natural Gas w/ CCS	3.60	4.25	4.57	4.68	4.75	4.79

Table S17: Fuel cost projections from 2020 to 2045. NGCC plants with CCS were assumed to have a 90% CO_2 capture rate and a capture and sequestration cost of $20/tone CO_2. (Source: 2020 EIA AEO Reference Case.[55])

S1.3.4 Network Topology

The Southeast model includes representations of four high-voltage transmission lines which connect, from source to sink, S_SOU to S_C_TVA, S_VACA to S_C_TVA, S_SOU to FRCC, and S_VACA to S_SOU. Transmission lines were assumed to be 500 kV, and line distances were computed by approximating the straight-line distance between the geographic center of each model region. Maximum transmission line capacity values were taken from Table 3-20 of the EPA IPM model documentation.[28] Transmission loss percentages were approximated as 0.01% of line distance. These parameters are summarized in Table S18.

Transmission network expansion was enabled in GenX, and all transmission lines were eligible for reinforcement up to 30 GW of capacity. New transmission lines were assumed to have a CRP of 40 years and after-tax WACC of 4.5%. Line reinforcement costs, adopted from Section 6.2 of the ReEDs Version 2019 documentation, were assumed to be $960 /MW-km for new 500 kV transmission lines.[35]

Transmission Line	Line Capacity (MW)	Line Distance (km)	Transmission Loss
S_SOU to S_C_TVA	5554	370	0.037
S_VACA to S_C_TVA	276	590	0.059
S_SOU to FRCC	3600	600	0.06
S_VACA to S_SOU	3000	500	0.05

Table S18: Transmission line representations in the Southeast model. (Source: Line capacities from the EPA IPM model.[28])

S1.3.5 Load Forecasts

State-level load data were derived from load profiles in the 2018 NREL Electrification Futures Study (EFS).[19] Load for even years (2020, 2030, 2040, and 2050) was taken directly from the study's data set, and load for odd years (2025, 2035, 2045) was approximated by interpolating data from the even-numbered years. Load profiles represent the "High" electrification and "Moderate" technological advancement scenarios, and leap days were removed.

State-level load data from the EFS data set were aggregated to approximate total load for each of the four model regions. Utility customer sales data from the 2018 Form EIA-861, labeled by BA, were used to approximate the percentage of each state's total load to be assigned to each model region.[58] Then, state-level load profiles from the EFS data set were aggregated using weightings proportional to these values to generate region-specific load profiles. The percentage of each state's load assigned to each model region is summarized in Table S19.

State	Percent of Total Customer Sales			
	S_C_TVA	**S_VACA**	**S_SOU**	**FRCC**
Tennessee	98.0%	0.0%	0.0%	0.0%
Alabama	26.2%	0.0%	73.8%	0.0%
North Carolina	0.6%	95.3%	0.0%	0.0%
South Carolina	0.0%	100.0%	0.0%	0.0%
Georgia	2.4%	0.0%	97.6%	0.0%
Florida	0.0%	0.0%	5.6%	94.4%
Mississippi	32.3%	0.0%	23.3%	0.0%

Table S19: Percent of statewide 2018 utility customer sales attributed to each of the four Southeast model regions, aggregated by balancing area. (Source: 2018 EIA-861.[58])

The region-specific load profiles were then adjusted to account for power interchange between BAs within the four Southeast model regions and those outside of them. There are nine interconnections to consider which allow for such power interchange: SOCO-MISO, DUK-PJM, CPLE-PJM, CPLW-PJM, TVA-AECI, TVA-EEI, TVA-LGEE, TVA-MISO, and TVA-PJM. EIA-930 form data downloaded via the EIA's hourly electric grid monitor includes hourly interchange, in MWh, between each of these BA interconnections, starting from July 2015.[59] Negative interchange values represent power flows into a BA, while positive interchange values represent power flows out of a BA. It also includes net-generation within each BA. The EIA-930 form data contained several missing values, so we used equivalent hours in future or past years as proxies for missing data. Hourly net interchange from the TVA model region was computed by taking the sum of hourly interchange between TVA-AECI, TVA-EEI, TVA-LGEE, TVA-MISO, and TVA-PJM. Hourly net interchange from the Carolinas model region was computed by taking the sum of hourly interchange between DUK-PJM, CPLE-PJM, and CPLW-PJM. Since the MISO BA is the only non-model BA connected to the S_SOU model region, hourly transfers from the SOCO BA to the MISO BA represent the entire external net hourly interchange in the S_SOU model region. Next, for the three model regions with net interchange, an hourly scaling factor was computed by taking the point-wise difference between net-generation and interchange and dividing by net-generation. We defined outlier hours as those with a scaling factor greater than 1.5 or less than 0.5, representing power flows into the region greater than 50% of the net-generation within that region in that hour, or power flows out of the region greater than 50% of the net-generation within that region in that hour, respectively. These outlier hours were replaced by the average of all hourly scaling factors excluding outlier hours in their respective regions. Next, the hourly scaling factors for each region were averaged across years to compute an average scaling factor for each hour. Finally, each hour in the annual load profile projections computed for each model region was scaled by its corresponding hourly scaling factor to obtain an interchange-adjusted representation of regional load.

S1.3.6 Variable Renewable Energy Capacity Factor Profiles

Seven years of historical capacity factor (CF) profiles (2007-2013) were generated for solar PV and wind resources using the methodology outlined in Brown and Botterud (2020).[33] We assumed a horizontal 1-axis-tracking PV array for solar PV resources and a Gamesa G126/2500 turbine at 100-meter height for wind resources.

EIA-923 data were used to compute historic monthly net-generation, in gigawatt-hours (GWh), of all run-of-river and reservoir hydroelectric plants in each of the four model regions from 2007-2013.[20] Monthly net-generation was then downscaled to hourly resolution by dividing monthly generation by the number of hours in each month (for leap years, non-leap year number of hours per month were used). Finally, the average hourly CF for each hydroelectric plant type in each model region was computed by dividing the hourly net-generation by the nameplate capacity of the respective hydroelectric plant type.

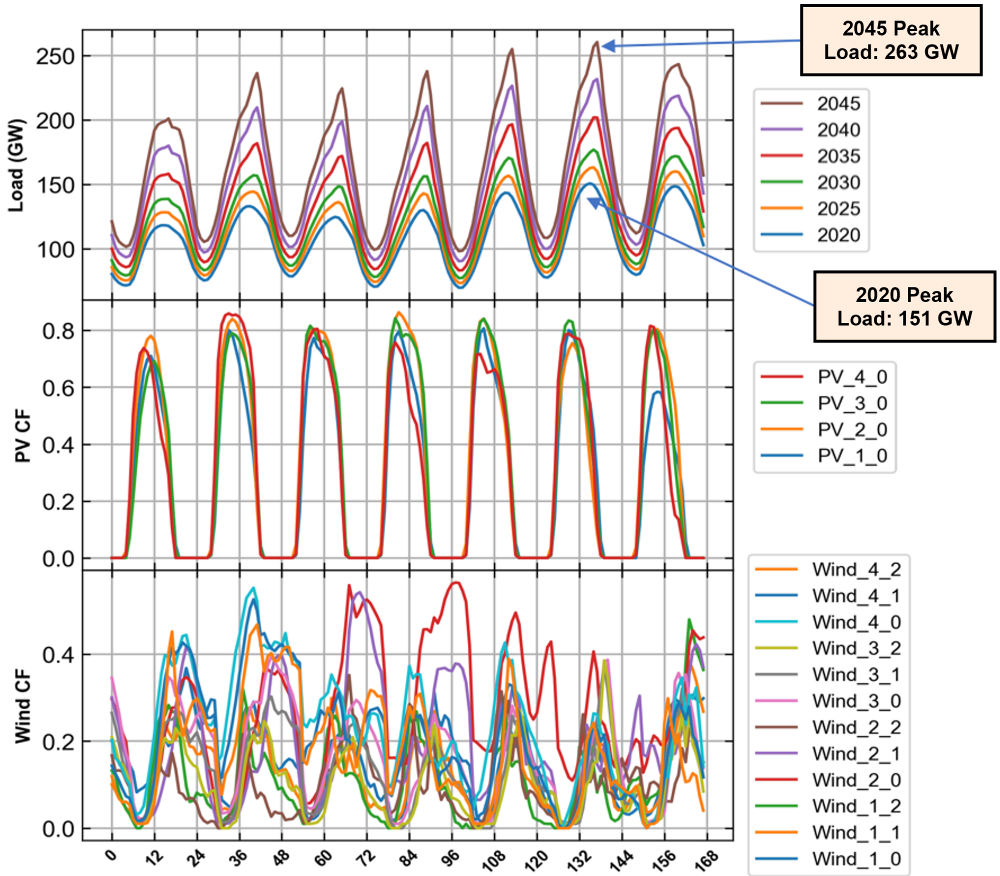

Figure S2: Load profiles (GW) and solar PV and wind capacity factor (CF) profiles for the model-wide peak load week, included as one of the extreme weeks in the model. Peak capacity grows from 151 GW in 2020 to 263 GW in 2045. Solar PV and wind CF profiles are named according to the convention PV_[Region]_0 and Wind_[Region]_[Bin], where 1, 2, 3, and 4 correspond to the S_C_TVA, S_VACA, S_SOU, and FRCC regions, respectively.

S1.3.7 Time Domain Reduction

Representative and extreme weeks were selected from among the seven years of CF and load profiles in order to reduce the required computational and memory requirements of GenX model simulations.

Extreme weeks were chosen from each of the four Southeast model regions. Average weekly CFs were computed for solar PV and wind resources. For solar PV resources, the week with the lowest average solar PV CF in each model region was included in the set of extreme weeks. For wind resources, we included an extreme week with the lowest average CF, selected from the bin with the lowest average CF over the whole seven-year duration. Finally, the week with the greatest hourly load in each model region was included in the set of extreme weeks, as well as the week with the greatest hourly total system load across the model regions (shown in Figure S2). Due to overlap, a total of nine unique extreme weeks were selected in this manner.

Representative period selection followed the methodology outlined in Mallapragada et al. (2018).[24] First, each time series was normalized to values between 0 and 1 (inclusive). Next, load and CF profiles were split into week-length groupings, and "stitched together" as in Mallapragada et al. (2018) to form 365 vectors, one for each week of the seven years represented by the historic VRE time series data (the six, year-long time series representing hourly load from 2020, 2025, ... , 2045 were repeated seven times so that they could be combined with the VRE time series data). Vectors corresponding to extreme weeks were dropped, and k-means clustering was applied to the set of remaining vectors to group them into clusters of similar weeks such that the total number of extreme weeks and clusters summed to 14, resulting in 5 clusters. The 5 representative weeks used in the model were selected from each cluster by choosing the vector with the lowest Euclidean distance from the cluster centroid.

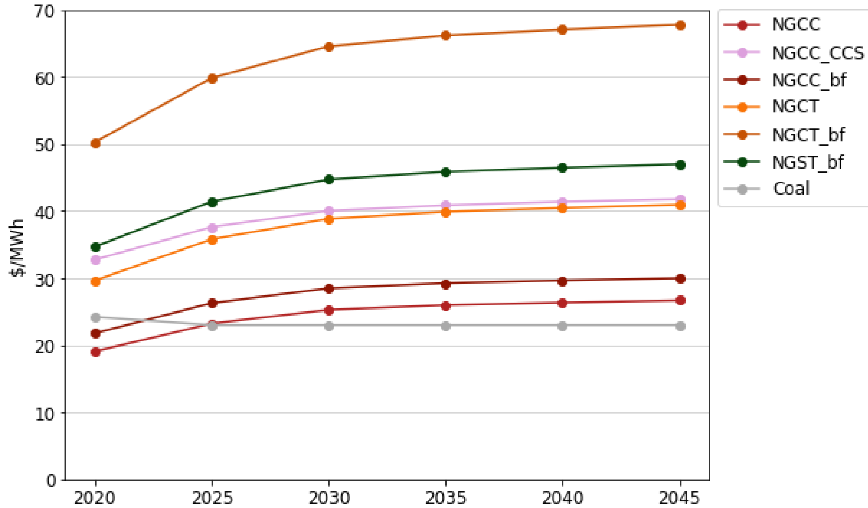

Figure S3: Marginal cost of generation of greenfield and brownfield (bf) thermal technologies in the S_C_TVA model region.

Assumption	Value
Dollar Year	2018
WACC	4.50%
CRP (Li-Ion)	20 years
CRP (Transmission)	40 years
CRP (All Other Resources)	30 years
NREL ATB Financials	Market Factor
NREL ATB Wind Class	Class 5
NREL EFS Technology Advancement	Moderate
NREL EFS Electrification	High
Number of Extreme Periods	9
Number of Representative Weeks	5
Value of Lost Load	$50,000

Table S20: Summary table of key model parameters and assumptions.

S2 Additional Results

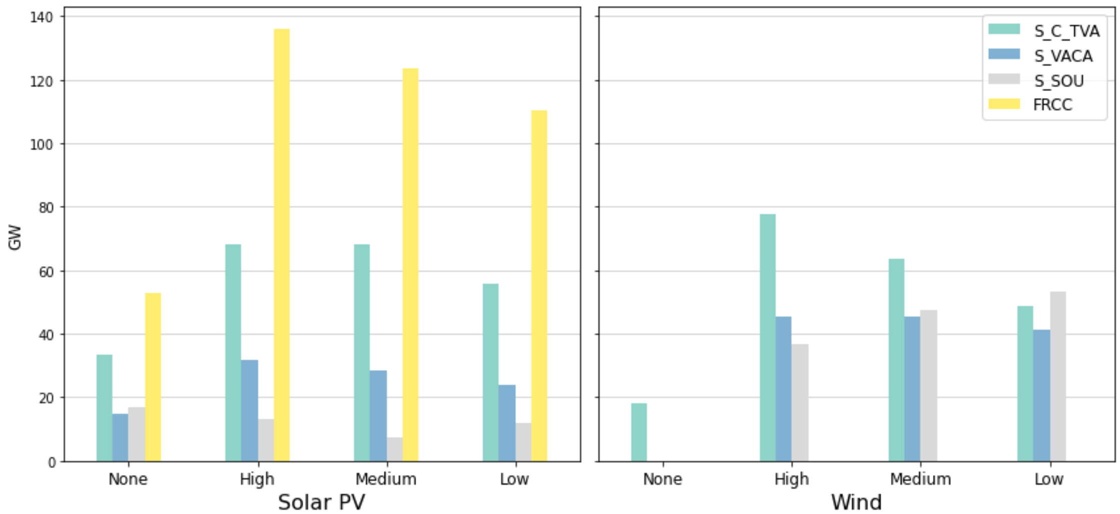

Figure S4: Regional deployments of solar PV and wind under the reference scenario (GW).

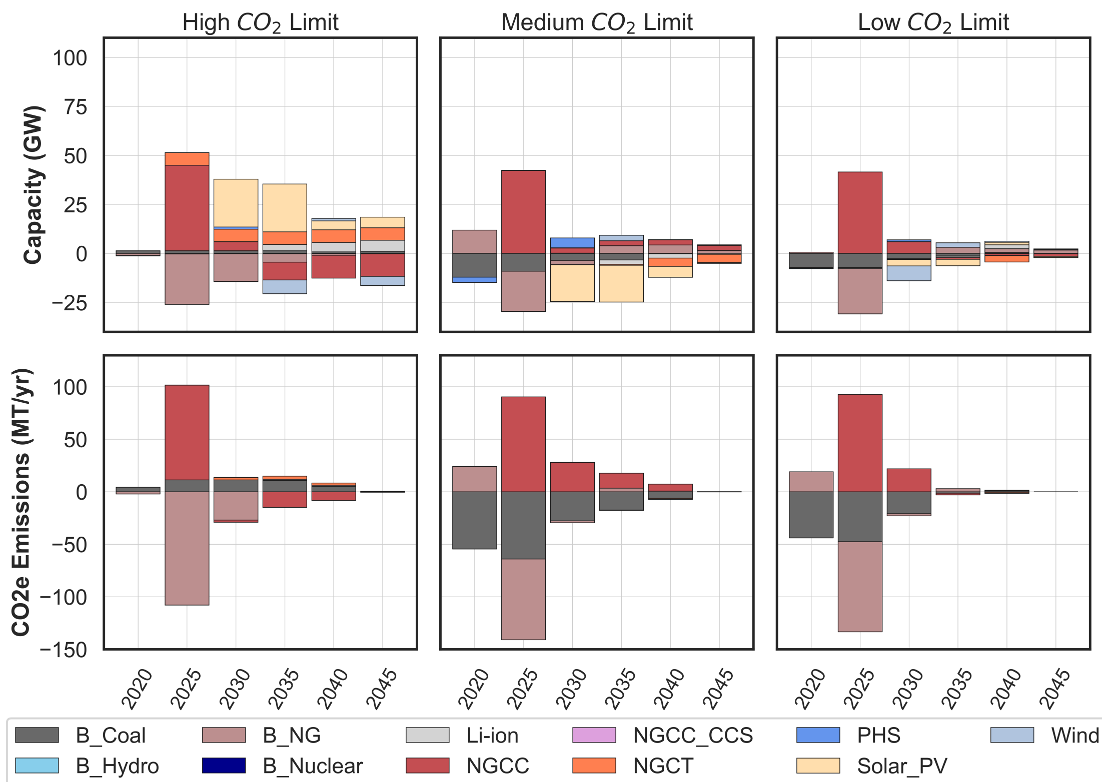

Figure S5: No New Natural Gas without CCS After 2025 – Changes in system-wide capacity (GW) and annual CO_2 emissions (MT) under the High, Medium, and Low policies with respect to the reference scenario.

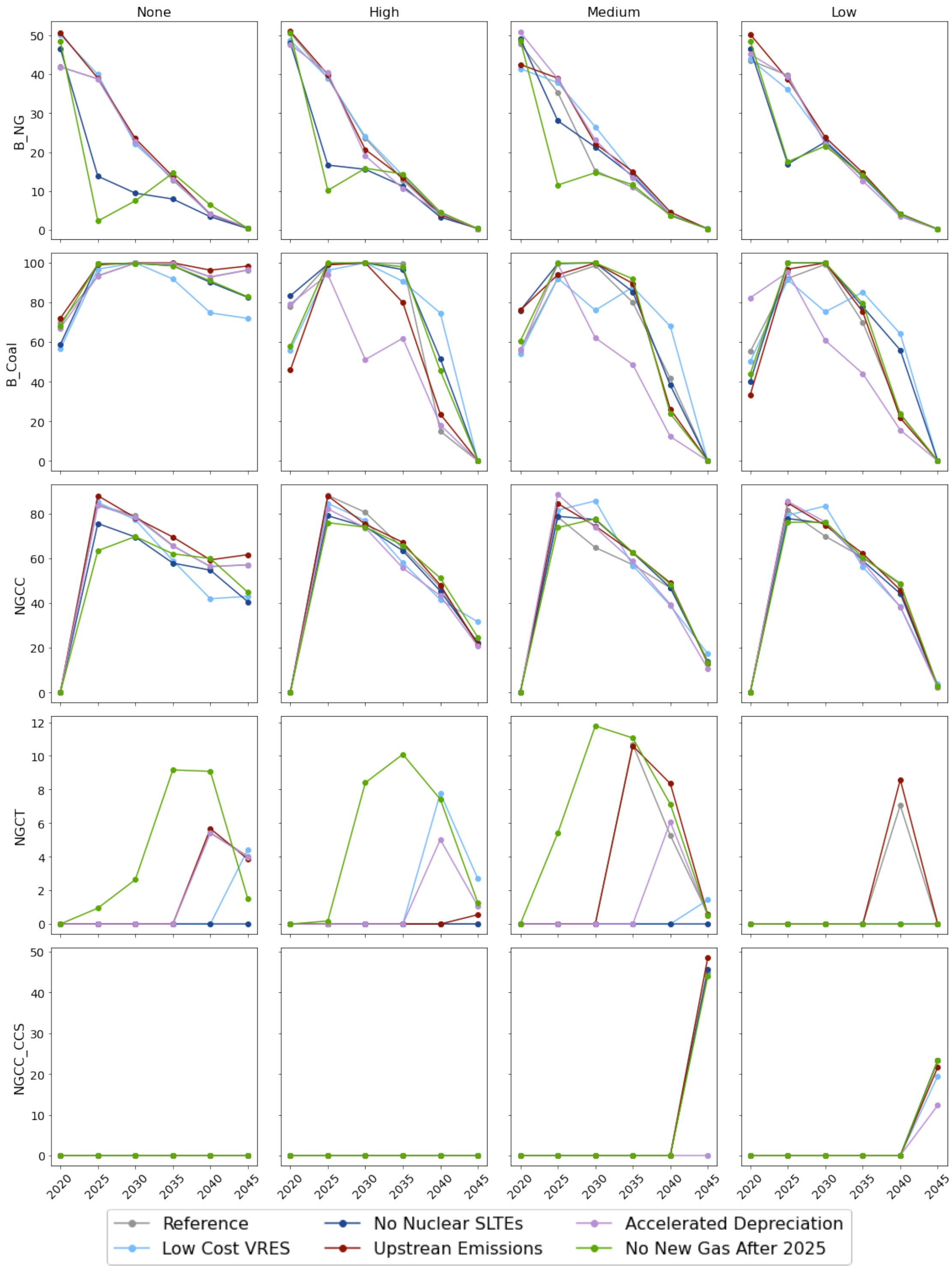

Figure S6: Average capacity factors (%) by CO_2 policy, thermal technology, model stage, and scenario.

Contact.

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