Climate-induced tradeoffs in planning and operating costs of a regional electricity system

Francisco Ralston Fonseca,[*,†] Michael Craig,[‡,†] Paulina Jaramillo,[†] Mario Bergés,[¶] Edson Severnini,[§] Aviva Loew,[†] Haibo Zhai,[‖,†] Yifan Cheng,[⊥] Bart Nijssen,[⊥] Nathalie Voisin,[#,⊥] and John Yearsley[⊥]

†*Engineering and Public Policy, Carnegie Mellon University, Pittsburgh, PA, 15213, USA*

‡*School for Environment and Sustainability, University of Michigan, Ann Arbor, MI, 48109, USA*

¶*Civil and Environmental Engineering, Carnegie Mellon University, Pittsburgh, PA, 15213, USA*

§*Heinz College, Carnegie Mellon University, Pittsburgh, PA, 15213, USA*

‖*Civil and Architectural Engineering, University of Wyoming, Laramie, WI, 82071, USA*

⊥*Civil and Environmental Engineering, University of Washington, Seattle, WA, 98195, USA*

#*Pacific Northwest National Laboratory, Richland, WA, 99354, USA*

E-mail: fralston@andrew.cmu.edu

Abstract

Electricity grid planners design the system in order to supply electricity to end users reliably and affordably. Climate change threatens both objectives through potentially compounding supply- and demand-side climate-induced impacts. Uncertainty surrounds each of these future potential impacts. Given long planning horizons, system planners must weigh investment costs against operational costs under this uncertainty.

Here, we developed a comprehensive and coherent integrated modeling framework combining physically-based models with cost-minimizing optimization models in the power system. We applied this modeling framework to analyze potential tradeoffs in planning and operating costs in the power grid due to climate change in the Southeast U.S. in 2050. We find that planning decisions that do not account for climate-induced impacts would result in a substantial increase in social costs associated with loss of load. These social costs are a result of under-investment in new capacity and capacity deratings of thermal generators when we included climate change impacts in the operation stage. These results highlight the importance of including climate change effects in the planning process.

Keywords

Power system modeling, Climate change, Climate impacts, Energy economics, Climate mitigation

Synopsis

Power system planning decisions that do not account for climate-induced impacts could result in a substantial increase in social costs associated with loss of load.

Introduction

Power system planners consider numerous uncertainties to ensure continued availability of reliable and affordable electricity. In the coming decades, uncertain climate-induced risks to the power sector may become an important consideration in the power system planning process. According to the Intergovernmental Panel on Climate Change (IPCC), average global temperatures are likely to rise 1.5° C above pre-industrial levels by 2052.[1] Meteoro-

logical variability, climatic extremes, and droughts will also likely increase.[2] Utilities have already started discussing adaptation strategies to address potential climate impacts on their grids,[3–5] which will manifest in several ways.[6,7] On the demand side, warming temperatures will likely result in changes in electricity consumption used for ambient heating and cooling.[8–14] These changes could result in increased total consumption and peak electricity demand. On the supply side, changes in streamflow could affect hydropower generation.[15–18] Also, decreased water availability, and increased water and air temperatures could reduce the capacity and efficiency of thermal units.[19–23] Climate change could also affect wind and solar resources, transmission assets, and other technologies essential to a zero-carbon system.[24–26] Recent events in the US and Europe have already revealed the vulnerabilities of the power system to such impacts.[27–29]

Given these aforementioned risks, a growing body of literature has analyzed how climate change might affect electric power systems.[30] Many studies have focused on impacts to individual components of the power system, such as electricity demand[8,9,11,13,14] or generation capacity.[20–22] However, because such studies do not take into account the interconnected nature of the power system, they do not represent the potential interactions between the different climate-induced impacts. More recent studies have used system-level operation models to aggregate impacts of climate change across components of the power system.[25,31–33] Yet, these studies have not typically integrated the planning stage into their analysis. They either use present configurations of the generator fleet or exogenous fleet configurations not directly linked to the climate-induced impacts represented. Additionally, some of the studies that have included the planning stage into their analysis[34–36] have not consistently integrated climate-induced impacts into their modeling framework, which could result in some biases in their results. For example, if a study represented uniform climate-induced impacts throughout the year, it may miss how the heterogeneous seasonal impacts could impact planning decisions.[34] A consistent integration into system-wide analyses is necessary to better comprehend the systemic risks a power grid faces due to climate change. An

important application is to understand potential tradeoffs between present planning costs and future operation costs under different climate change scenarios. These tradeoffs are critical because planning horizons in the power sector can span several decades – the typical service life of most energy assets – and associated investments can extend into the billions of dollars.

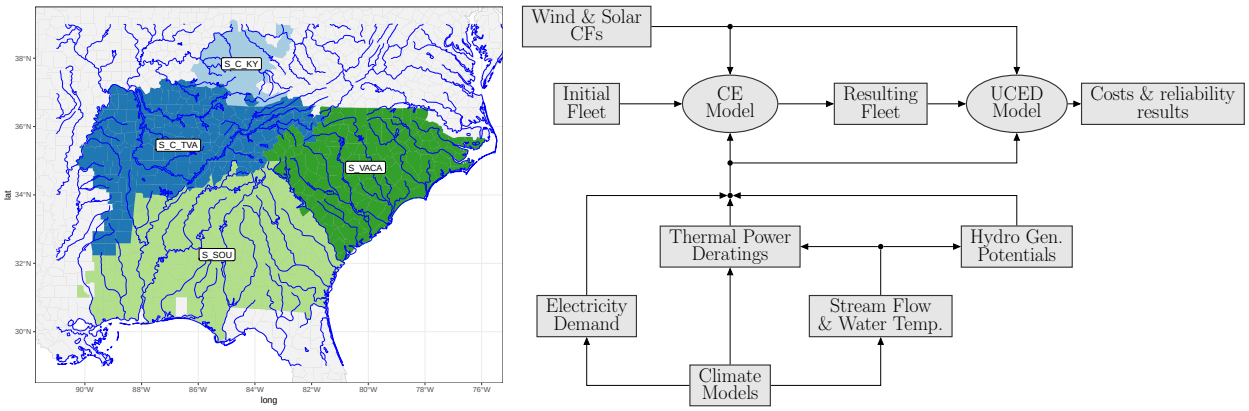
In a previous study, we integrated climate change impacts into a capacity expansion model of the southeast U.S. in order to analyze how climate-induced impacts could change investment decisions.[37] In the current study, we expand on this previous work by including in our modeling framework a detailed unit commitment and economic dispatch (UCED) model to simulate power system operations. We use this expanded modeling framework to control whether planning and/or operations account for climate change. By doing so, we are able to investigate key questions relevant to system planners, including (1) if planners ignore climate change, how will their systems fare operationally when we include climate change impacts?, and (2) if planners account for climate change, what are the excess costs if we do not include include climate change impacts? Through this experimental design, we bound the tradeoffs between including and not including climate impacts in planning decisions given the uncertain operational consequences of those decisions. This bounding exercise provides crucial information to system planners and policymakers deciding whether to plan for climate change.

We rely on a comprehensive and coherent integrated modeling framework to analyze climate-induced tradeoffs between planning and operation costs in the power grid under Representative Concentration Pathway (RCP) 4.5 by midcentury (Figure 1b). We simulated the different climate-change risks in a consistent way[23] by considering the same ensemble of climate models, concentration pathways, and time horizons. We applied our method to a case study of the SERC Reliability corporation in the Southeast U.S., but the framework can be used for planning and operation purposes by any electricity system. We used simulated climate inputs[38,39] within a chain of different models to simulate synchronous

climate-induced impacts on hourly electricity demand,[14] daily river flows and water temperatures,[40–45] hydropower potential, and capacity deratings for thermoelectric power plants.[46–48] We integrated these impacts into a capacity expansion (CE) model[37] to create future generator fleets, then fed these impacts and fleets the UCED model to simulate power system operations.

Methods

We used a two-stage optimization modeling framework to quantify the potential tradeoffs in planning and operating power systems under different scenarios of future climate impacts. To quantify planning costs, in the first stage (*Planning stage*, which was the focus of our previous study[37]), we used a CE model to optimize the composition of generator fleets in 2050 twice, including and excluding future climate change impacts. Our main results assume no CO2 emission policy. In the second stage (*Operation stage*), we used a UCED model to optimize operations of the two CE-derived generator fleets in 2050 twice, with and without impacts of climate change. In planning and operations, climate change impacts are derived from RCP 4.5. This experimental design yielded four scenarios, or pairwise combinations of two sets: (1) accounting and not accounting for climate impacts in planning and (2) accounting and not accounting for climate impacts in operations (Table 1). To test the sensitivity of our results to CO_2 emission policies, we repeated the above experimental design under a 50% and 80% reduction in CO_2 emissions from 2015 by 2050 (see resulting fleets in Section 1.2 in SI). Because the purpose of this analysis is to isolate the potential costs of climate-induced risks on the power system, we did not account for other changes that may affect the operations of the power system (e.g., changes in population or economic growth).



(a) (b)

Figure 1: (a) Map of study area (b) Simplified diagram of the modeling framework (a more detailed diagram is available in the SI)

Table 1: Scenario definition

	Scenario name	Planning stage (2015–2050)	Grid operation stage (2050)
1	Ignore CC/no CC effects	Ignore climate change risks on demand and supply	No climate change impacts on demand and supply
2	Plan for CC/CC effects	Include climate change risks on demand and supply (RCP 4.5)	Climate change affects demand and supply (RCP 4.5)
3	Plan for CC/no CC effects	Include climate change risks on demand and supply (RCP 4.5)	No climate change impacts on demand and supply
4	Ignore CC/CC effects	Ignore climate change risks on demand and supply	Climate change affects demand and supply (RCP 4.5)

Area of study

Our analysis focused on the SERC Reliability Corporation (SERC) (Figure 1a), one of the North American Electric Reliability Corporation (NERC) subregions. SERC has a diverse generation portfolio (that includes fossil-based power plants and a significant contribution of hydroelectricity) and a demand profile with peaks in both summer and winter. According to the National Climate Assessment, SERC is particularly vulnerable to some of the expected impacts of climate change.[2] To better represent spatial differences in SERC, we used the four subregions defined in EPA's Integrated Planning Model.[49]

Climate Simulations

To represent historical weather conditions, we used weather data from the University of Idaho Gridded Surface Meteorological Data (gridMET) dataset[50] for the years 1979 – 2015. We then disaggregated the daily data to hourly values using METSIM (Meteorology Simulator).[51]

To represent weather conditions under climate change in 2050, we used simulated projections of weather variables from twenty different Global Circulation Models (GCM) for the year 2050 from the Coupled Model Intercomparison Project 5 (CMIP5),[38] spatially downscaled using the Multivariate Adaptive Constructed Analogs (MACA) method.[39] In addition, we again disaggregated these daily projections to hourly values using METSIM. We selected the output of these climate models under representative concentration pathway RCP 4.5. For more details on the climate data use, see the SI.

Electricity demand

We used an econometric model to estimate the projections of SERC's electricity hourly demand in future years under different climate change.[14,37] We used the downscaled projections of hourly air temperature of the twenty different GCMs under RCP 4.5 described previously

to simulate future electricity demand under climate change. In order to create a comparable reference case of historical demand (not including impacts of climate change), we used this model with historical air temperature data (1979 – 2015) to estimate historic hourly electricity demand.

For each of the four subregions in SERC considered in this study, we averaged hourly air temperature from the two most populous cities. To control for unobserved factors affecting electricity demand in each hour of the day, the model included fixed effects coefficients for each hour of the day in different seasons and different types of day (workday or weekend). Annual long-term trends were modeled using fixed-effects for each year in the historical data set. This way, the model was capable of controlling for changes in the demand in electricity caused by economic and technological shifts in our historical dataset. In this analysis, we assumed that other factors that could affect our projections of demand (such as changes in economic activity and population) remained constant at their estimated 2015 levels. Doing so allows us to isolate the impacts of climate change on electricity demand and, in turn, on planning and operational trade-offs, the goals of this analysis.

Hydrological simulations

To simulate regulated daily river flows and water temperatures in the study region, we used a physically-based modeling framework. This process-based modeling approach consists of three models. First, we used a macroscale, spatially distributed hydrological model, the Variable Infiltration Capacity (VIC) model,[40] to simulate runoff. Second, the runoff was used as an input into a river routing model, the Model for Scale Adaptive River Transport (MOSART),[41] dynamically coupled to a spatially distributed water management model (WM),[42,43] to simulate reservoir storage and regulated streamflow. Third, surface meteorological data and simulated hydrologic conditions were used to simulate regulated river temperatures, using a one-dimensional stream temperature model, the River Basin Model (RBM),[45] coupled with a two-layer reservoir thermal stratification module.[44] We ran these

models at a grid resolution of 1/8 degree ($\sim$ 12 km) using the climate forcing data for the year 2050 from twenty different GCMs from CMIP5,[38] spatially downscaled using the MACA method.[39]

Thermal deratings

To simulate weather-induced deratings of thermoelectric power plants in our model, we first used the Integrated Environmental Control Model (IECM) to estimate typical response curves of thermal generators to changes in weather variables, stream temperatures, and stream flow.[46,47] The estimated response curves modeled the effects of weather variables, stream temperatures, and stream flow on a power plant's available capacity and water withdrawal. For each type of cooling system, the response curves use the more significant ambient variables.[46] Additionally, response functions are dependent on cooling system design characteristics. For each cooling system, we chose design parameters values at the middle of the range reported in a previous study.[46] For thermal power plants with once-through cooling, we also simulate the maximum operating capacity that would not cause water temperatures downstream of the power plant to rise above up environmental regulations. More details about the simulation of thermal deratings are available in the SI.

Hydropower generation

To simulate the potential effects of climate change on the available energy at hydropower plants, we combined historical data of energy produced by the hydropower plants in the SERC region with the simulations of daily river flows from the VIC and MOSART-WM models described above. We assumed that the potential energy available at each hydropower plant is proportional to the regulated stream flow simulated by hydrological models at the plants location.[52] Within the optimization model, the actual generation decision for each hydro generator is limited by both this potential and the installed capacity of the power plant. To capture impacts of climate change, we simulated 20 different instances of daily

hydropower potential (one for each GCM). For simulations that do not consider the impacts of climate change, we used the historical monthly average generation for each power plant from EIA. Using a monthly average value for the scenarios "without climate change" ignores the inter-annual variability in hydro generation. However, because hydro generation is a relatively small part of total generation in SERC, this simplification does not impact our results substantially. More details about the simulation of hydropower potentials are available in the SI

Wind and solar generation

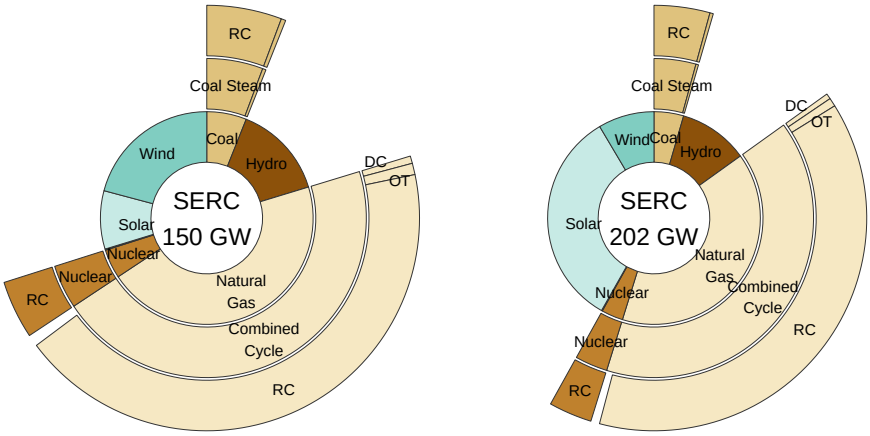
Forecasting wind and solar resources under climate change remains a significant challenge, particularly at an hourly resolution. New initiatives, e.g. High Resolution MIP,[53] are beginning to release downscaled wind and solar resource data, but available data is limited, e.g. wind speeds are available at the surface at 3-hourly resolution. Other research has used numerical weather prediction models to downscale wind and solar resources,[26] but such models are computationally-intensive and outside our scope. Furthermore, past studies have disagreed on the direction of change in solar and wind resources.[30]

Given these significant challenges, we capture spatial and temporal variability in output among wind and solar farms using historical simulated wind and solar generation profiles from the U.S. National Renewable Energy Laboratory (NREL).[54,55] We aggregated the original sub-hourly generation data to hourly increments by calculating the average generation values for all time steps in each hour. We assigned the generation profiles of these individual sites to the wind and solar power plants in our generator fleet in order of decreasing capacity factor, assuming existing projects tap the greatest available resources. To improve the computational efficiency of the model, we combined wind and solar units into single equivalent wind and solar units by summing up their capacities and hourly generation profiles within each subregion. Hourly generation profiles serve as the upper bounds on hourly generation from the combined wind and solar units. More details are available in the SI.

Capacity expansion

The fleet configurations in 2050 used in this study were determined in a separate study[37] using a capacity expansion (CE) model integrated in our modeling framework (see Figure 1b). The CE model is a mixed integer linear programming (MIP) model that chooses how to add new capacity to the power system in order to minimize the sum of annualized fixed investment costs and variable operating costs of the final generator fleet. Its main decision variables are investment in new power plants. The model takes into account system-wide constraints, including matching hourly electricity generation to hourly demand, and meeting planning reserve requirements (which was set at 14% above projected peak demand values[37]). The fleet configurations were determined using the same ensemble of climate models and concentration pathways used to simulate climate-induced effects on supply and demand in this study. In our main results in this study, we used two configurations of the generator fleet in 2050, neither of which included a CO_2 emission policy. The first fleet (Figure 2a) was derived through CE simulations that did not consider the effects of climate change on future supply and demand. Electricity demand was simulated using historical climate data; hydro generation potentials were equal to monthly historical averages; and we included no climate-induced capacity deratings for thermal power plants. The second fleet (Figure 2b) was created including the simulated effects of climate change on supply and demand under RCP 4.5 by 2050 in the CE model. From the first to second fleet, installed capacity increased by roughly 35% driven by greater peak demand and decreased available thermal capacity under climate change. In response to these trends, solar deployment also increased, further driving up installed capacity.

Additionally, we also performed a sensitivity analysis assuming two CO_2 emission policies: 50% reduction, and 80% reduction by 2050 compared to 2015 levels. We repeated the steps described above in each of these sensitivity analyses, which resulted in four additional fleets (two for each CO_2 emission policy case, see section 1.2 in the SI). A detailed description of the capacity expansion model and output future generator fleets is available in Ralston



(a) Ignore CC (b) Plan for CC

Figure 2: Configurations of the generator fleet in 2050 described in Ralston Fonseca et al.. Both fleets were created assuming no limits on CO_2 emissions. Numbers in the center of each plot show the total installed capacity in 2050. The inner layer of the pie chart shows the breakdown into the different fuel sources used by the power plants in SERC. The middle layer shows the types of generating technologies – where applicable – used for each type of fuel source. The outer layer presents the cooling technologies used in the respective thermoelectric generators. The codes "OT", "RC", and "DC" stand for, respectively: once-through cooling, recirculating cooling, and dry cooling.

Unit Commitment and Economic Dispatch

To analyze the tradeoffs between planning and operational costs under different climate change assumptions, we used a unit commitment and economic dispatch (UCED) model.[33,56] The UCED model is a mixed integer linear programming (MIP) model that optimizes plant-level electricity generation in order to minimize operational costs while meeting electricity demand and generator-level unit commitment constraints. Operational costs consist of the sum of variable electricity generation cost, start-up cost, and estimated cost due to loss of load. We implemented a customized version of this model that included climate induced generation constraints in thermal and hydro generators, and impacts of climate change in electricity demand. A detailed formulation of the UCED model is available in the SI.

The UCED model ran sequentially for 365 daily simulations of hourly dispatch to build

a full 8760-hour simulation of the generation at individual plants for a simulation year representing 2050. In order to account for inter-day generator operations, we executed each daily iteration of the UCED model with a 24 hour optimization window plus a 24-hour look-ahead period. The solution of the first 24 hour period determines the initial conditions for the following UCED iteration. When optimizing operations with climate change impacts, we ran one full annual UCED dispatch simulation for each of the twenty climate model outputs in our dataset for the year 2050.

Each of the twenty climate simulations resulted in distinct time series with 8760 values of hourly electricity demand, and 365 values of daily thermal capacity deratings and hydropower potential. By running our UCED for 2050 from 20 GCMs, we capture most mid-century inter-annual variability in mean daily, maximum daily, and total annual temperature while balancing the computational cost of our UCED model (see section 1.3 SI). We repeated a similar approach when optimizing operations without climate change effects. In this case, we simulated twenty distinct time series of hourly electricity demand by sampling the weather conditions of twenty unique years in our historical dataset (1979 – 2015) that are meant to represent meteorological conditions in 2050 in the absence of climate change. On the supply-side, we assumed that hydro generation potentials were equal to historical averages, and thermal power plants experienced no climate-induced capacity deratings. This process resulted in twenty different dispatch simulations in each of our four scenarios (Table 1). For more details, see the SI.

Loss of load

To estimate potential impacts of climate change on reliability and cost, we quantified loss of load (LOL) as unserved electricity demand in the supply/demand equation of the UCED model (see section 1.9 in SI). We also calculated the loss of load probability (LOLP) by dividing the number of hours in which any LOL occurred by the total number of simulated hours in each UCED simulation. To quantify the cost of these outages, we used the value of

lost load (VOLL), which we based on values calculated for the Electric Reliability Council of Texas (ERCOT).[57] We updated these values to 2015 currency[58] and adjusted them to a system-wide value to the southeast U.S. This results in a VOLL of 3,018 $/MWh (2015 USD). For more details, please see the SI.

Normalized cost of energy

The normalized cost of energy is analogous to the levelized cost of energy (LCOE), but in this study it is used to perform a consistent comparison between different generator fleets under different scenarios. To compute the normalized cost of energy, we summed up all annualized fixed and variable costs and divided by the total annual electricity consumption (D_{2050}) in each scenario. The set of costs $\mathcal{C}$ includes: capital expenditures (capex) costs (annualized using a 5% discount rate and standard power plant lifetimes), annual fixed operation and maintenance (fixed O&M) costs, annual variable O&M costs, fuel costs, and annual LOL costs. We computed annual LOL costs by multiplying annual LOL by the VOLL. See SI for more details.

$$\text{Normalized cost of energy [\$/MWh]} = \sum_{cost \in \mathcal{C}} \frac{cost \text{ [\$/year]}}{D_{2050} \text{ [MWh/year]}} \tag{1}$$

To further understand tradeoffs between planning and operations under climate change, we estimated an implied cost of avoiding observed LOL in scenario *Ignore CC/CC effects*. Planning for climate change potentially increases investment and operational costs; not planning for climate change potentially yields poor operational performance, e.g. due to lost load. Our implied cost metric equals the difference in costs divided by the difference in lost load between scenarios. Comparing implied cost to the VOLL indicates whether increased costs from planning for climate change are justified by their subsequent operational value in avoiding lost load. To estimate the implied cost, we computed the difference in annual investment and operating expenses between scenarios *Plan for CC/CC effects* (*cost*) and

Ignore CC/CC effects ($cost'$). Then we divided this monetary value by the difference in LOL between scenarios *Plan for CC/CC effects* (LOL) and *Ignore CC/CC effects* (LOL') (see Equation 2).

$$\text{Implied Cost [\$/MWh]} = \frac{\sum_{cost \in \mathcal{C} \setminus \text{LOL}} cost - \sum_{cost' \in \mathcal{C} \setminus \text{LOL}} cost' \text{ [\$/year]}}{LOL - LOL' \text{ [MWh/year]}} \tag{2}$$

Results

Figure 3 compares the normalized cost of energy (in \$/MWh) of the four scenarios analyzed. Not planning for climate change can result in a substantially higher normalized cost of energy than other scenarios. In scenarios where the planning stage did not account for climate-induced risks, the average normalized cost of energy was 36.8 \$/MWh (*Ignore CC/no CC effects*) and 99.3 \$/MWh (*Ignore CC/CC effects*) (2015 USD), or \$24.1 billion/year and \$66.9 billion/year, respectively. In the scenarios where planning did account for climate-induced risks (*Plan for CC/CC effects* and *Plan for CC/no CC effects*), the average normalized cost of energy was 40 \$/MWh (\$26.1 billion/year). Planning for climate change resulted in average capex costs of approximately 12.7 \$/MWh (\$8.4 billion/year), roughly 60% higher than when ignoring climate change (8 \$/MWh or \$5.3 billion/year). However, planning for climate change resulted in smaller variable costs because the expansion policy builds more solar generators. Since solar (and wind) have near-zero marginal operating costs, more solar generation reduces variable costs. In scenarios *Plan for CC/no CC effects* and *Plan for CC/CC effects*, average variable costs (fuel + variable O&M) are approximately 19.5 \$/MWh (\$ 14.5 billion/year). In scenarios *Ignore CC/no CC effects* and *Ignore CC/CC effects* average variable costs are approximately 20.5 \$/MWh (\$ 15.1 billion/year). The average total cost of LOL dominates the normalized cost of energy in scenario *Ignore CC/CC effects* (Figure 3). In this scenario, the total cost of LOL accounts for 64% of the normalized cost of energy, which makes this scenario the most costly.

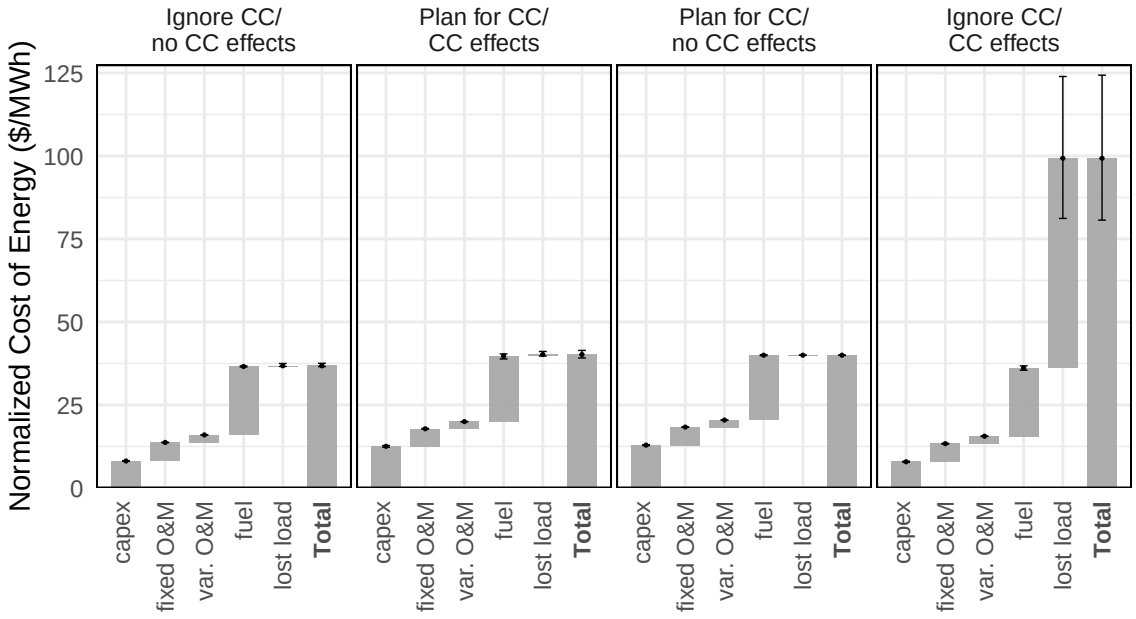


Figure 3: Comparison of normalized costs of energy in 2050 in the four scenarios. The values are the average of the simulations using data from twenty different GCMs. Error bars represent the 90% uncertainty range of each component over the twenty GCM simulations.

Given the importance of the total cost of LOL in our results, we estimate the implied cost of avoiding the LOL in scenario *Ignore CC/CC effects* (see Methods). According to our results, the average implied cost of avoiding the LOL in scenario *Ignore CC/CC effects* would be approximately 175 $/MWh, or 6% of the VOLL used in Figure 3. This result suggests that the cost (in $/MWh) of planning for climate change and thus avoiding LOL is substantially lower than literature VOLL values, some of which reflect consumers' willingness to pay to avoid outages.

Figure 4 shows average total generation in 2050 from the twenty UCED simulations in each scenario. In the scenarios that included climate change effects in the UCED model, total annual electricity consumption was approximately 673 TWh, or 3% higher than in the scenarios that did not account for climate change in the UCED model. Most of this increase in consumption was concentrated in the summer, when demand was 16% higher. Conversely, electricity consumption in the winter was approximately 3% lower in the scenarios that include climate impacts in the UCED model.

In the summer, RCP 4.5 meteorological conditions resulted in climate-induced capacity deratings of natural gas power plants. In scenario *Plan for CC/CC effects*, fleet planning partly offset these climate-induced deratings by investing in more solar power. Solar power plants in the southeast U.S. typically have higher power output in summertime compared to wintertime (see section 1.5 in SI). By having more solar energy available, the system is able to supply virtually all electricity demand. Conversely, in scenario *Ignore CC/CC effects*, fleet planning did not account for climate-induced deratings of natural gas power plants. As a result, the cost-minimization solution in the capacity expansion model relied on natural gas investments to meet demand and did not invest heavily in solar plants. When the natural gas plants suffered deratings during summertime under RCP 4.5 conditions, significant LOL occurs. Specifically, LOL equals roughly 12 TWh in the summertime (average of the UCED simulations for 2050 using data from twenty GCMs).

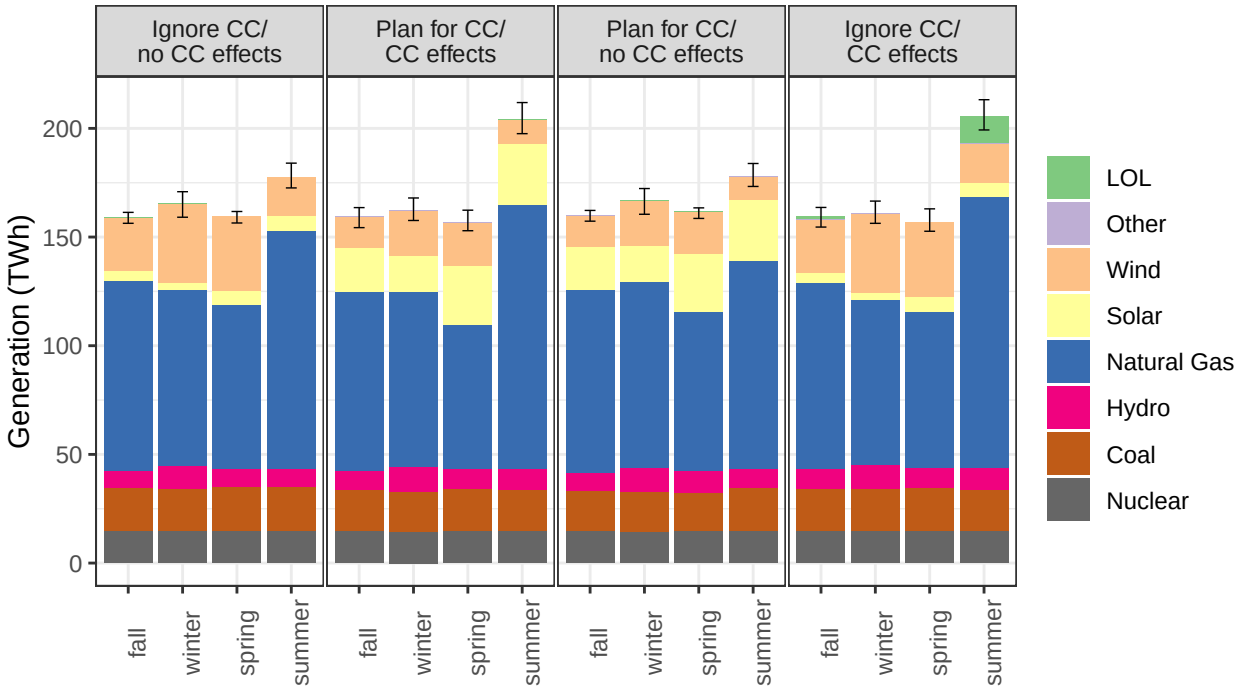
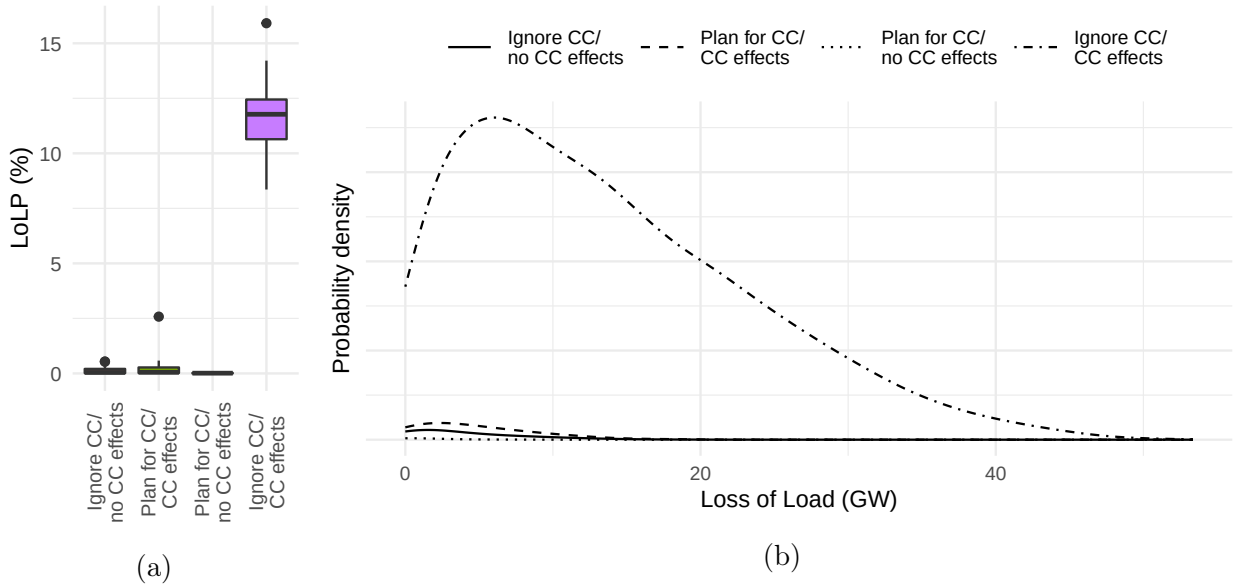


Figure 4: Comparison of the generation by source in each season and scenario. Generation values are averages over the twenty annual simulations in each scenario. Error bars represent the 90% uncertainty range of the total generation over the twenty GCM simulations.

Loss of load probability

Figure 5a shows the distribution of LOLP in each of the four scenarios. LOLP quantifies the expected number of hours in the year when any LOL occurs in our simulations. The scenarios (*Plan for CC/no CC effects* and *Plan for CC/CC effects*) in which capacity expansion accounted for climate-induced changes in demand and supply of electricity have low LOLPs. In the scenario *Plan for CC/no CC effects*, in which we included climate change impacts by 2050, the system has excess capacity, which results in approximately zero LOLP. In the scenario *Plan for CC/CC effects*, fleet expansion decisions were sufficient to cope with the estimated climate change effects by 2050, resulting in low LOLP (0.27%). Similarly, in scenario *Ignore CC/no CC effects*, LOLP is small (0.14%). Unlike these other three scenarios, scenario *Ignore CC/CC effects* had average LOLP levels of approximately 12%, corresponding to roughly 1,050 hours in 2050 in which the system cannot meet the full load. This high value of LOLP arises from two interrelated climate-induced constraints that were not considered in the planning stage: greater electricity demand and thermal deratings.

Figure 5b compares the kernel densities of the LOL values in the four scenarios simulated. Areas under each curve are scaled in order to better represent the different average probabilities in each scenario. As expected, the density plot for scenario *Plan for CC/no CC effects* show virtually probability zero of any LOL events. The density plots for scenarios *Ignore CC/no CC effects* and *Plan for CC/CC effects* present similar distributions of LOL events. Both distributions have low probabilities of any type of shortage event and the average LOL in these two scenarios is approximately 3.8 GW and 4.5 GW, respectively. *Ignore CC/CC effects* has a wider distribution than the other scenarios, with an average LOL of 14 GW and a 2% probability that LOL surpasses 23 GW (17% of the average peak demand value in this scenario).



(a) (b)

Figure 5: (a) Comparison of the loss of load probability (LOLP) in the four scenarios simulated. These values represent the expected number of hours in the year when a loss of load (LOL) event of any magnitude happened in our simulations. The boxplots in each scenario were compiled by simulating 8760 hours in the year. The range in the boxplots represents the different values compiled in the twenty different climate simulations in each scenario. (b) Comparison of the kernel densities of LOL in the fours scenarios simulated. Areas under the four curves are scaled in order to represent the different values of the overall LOLP in each scenario.

Drivers of loss of load

To quantify the drivers of LOL in *Ignore CC/CC effects*, we used the following heuristic: LOL are driven by thermal deratings first and under-investment in capacity second. At each time step, we measured the amount of lost load (X MWh) and the amount of deratings from all thermal generators in the fleet (Y MWh). Then we defined the component of lost load driven by thermal deratings at as $W = \min(X, Y)$ and the amount due to capacity under-investments as $Z = \max(0, X - Y)$. Thus, capacity under-investment implicitly accounts for climate-driven demand increases. Figure 6a shows the breakdown of the average LOL (in GW) that results from thermal deratings and under-investments in capacity. Capacity under-investment account, on average, for approximately 70% of the amount of LOL. Thermal deratings account for approximately 30%.

Figure 6b shows the joint density plot of the two components in scenario *Ignore CC/CC effects*. Capacity under-investment are responsible for larger LOL events that happen infrequently, while thermal deratings lead to smaller but more frequent LOL events. The mode of the distributions is located at a point where thermal deratings account for approximately 3 GW of LOL while capacity under-investment are close to zero. LOL values driven by thermal deratings have a maximum value of approximately 7 GW. Simulated LOL in scenario *Ignore CC/CC occurs* could total over 35 GW in some low probability events (see Figure 5b). Figure 6a shows that these low probability events would be driven mostly by under-investment in installed capacity.

Sensitivity analysis on planning with CO_2 emission targets

In our previous study, we also performed a sensitivity analysis of the fleet expansion simulations imposing 50% and 80% reduction in CO_2 emissions by 2050[37] (compared to 2015). Adding the 50% reduction target resulted in fleets with installed capacity 2% (*Ignore CC*) and 3% (*Plan for CC*) larger than the fleets designed without this emissions constraint (see Figure S3 in SI). This small increase in installed capacity was a result of additional deploy-

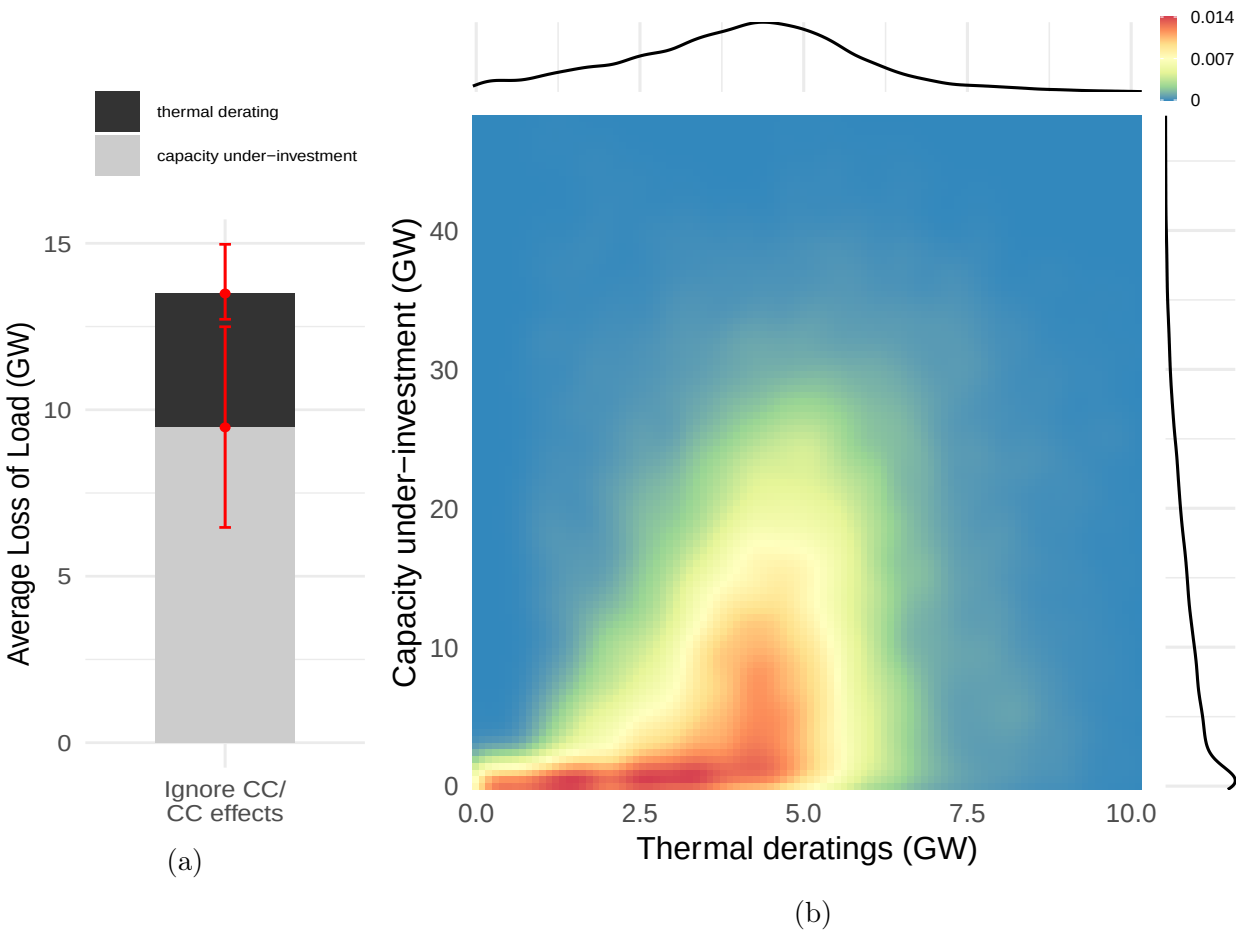


Figure 6: Decomposition of the LOL values in scenario *Ignore CC/CC occurs*. The thermal derating component corresponds to LOL events that occurred because of the deratings of thermal generators. The capacity under-investment component corresponds to those LOL caused by the lack of installed capacity on the system. (a) shows the average value of these components. The red error bars represent the range of values of each component over the twenty GCMs simulated. (b) shows the two-dimensional probability density function of the two components. Red colors represent higher frequency events, while blue colors represent lower frequency events. The marginal densities of each component are also illustrated in the plot.

ments of solar and wind in order to meet the emissions target. Cost and reliability results with this CO_2 emission constraint were similar to the ones presented in Figures 3 – 6 (see Figure 7, Table 2, and section 2 in SI). On the other hand, the fleets designed with 80% reduction in CO_2 emissions were substantially different[37] from the ones planned without CO_2 limits (see Figure S3 in SI). When imposing an 80% reduction in CO_2 emissions, there was a large increase of renewables in the fleet to meet the emission target. Resulting fleets were 68% (*Ignore CC*) and 47% (*Plan for CC*) larger than fleets designed without emission constraints. This increase in installed capacity resulted in an increase in capital expenditure costs (see Figure 7 and Table 2). Furthermore, the investments in renewable energy (at the expense of natural gas investments) reduced the vulnerability of the fleets to climate change, so the cost of LOL in scenario *Ignore CC/no CC effects* is 93% less than for our results without CO_2 limits (Figures 3 and 7). Because of greater capex and lower LOL costs, the scenarios *Ignore CC/CC effects* and *Plan for CC/no CC effects* had similar costs (within 1%). Conversely, without a CO_2 cap, scenario *Ignore CC/CC effects* had costs 148% greater than scenario *Plan for CC/no CC effects* (Figure 3).

Discussion

Our paper demonstrates that climate change could significantly reduce the reliability of future power systems if system planners do not account for climate change in their planning processes. Planning agents usually use standard target levels of reliability metrics to design the expansion of the electricity grid. For example, an acceptable target level of LOLP is 0.1 days/year.[59] For the fleets planned without CO_2 constraints, the results from the scenarios *Ignore CC/no CC effects*, *Plan for CC/CC effects*, and *Plan for CC/no CC effects* all reached levels of LOLP close to this target. However, scenario *Ignore CC/CC occurs* results in levels of LOLP of 12%, which would be an unacceptable level of outages. Outages in scenario *Ignore CC/CC occurs* were also of longer duration (115% longer on average than in the first

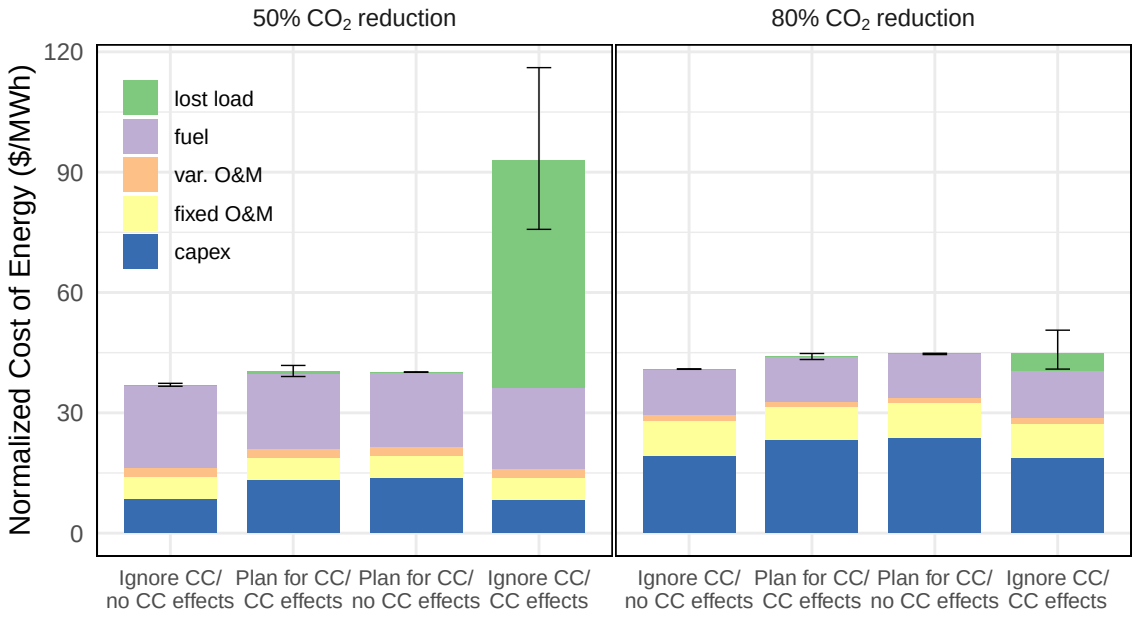


Figure 7: Comparison of normalized costs of energy in 2050 of the fleets planned with 50% and 80% reductions in CO_2 emissions (compared to 2015). The values are the average of the simulations using data from twenty different GCMs. Error bars represent the 90% uncertainty range of the total cost over the twenty GCM simulations.

two scenarios, see section 2 in SI) and of larger magnitude (200% greater than in the first two scenarios, see Figure 5b). These high levels of LOLP resulted in substantial costs to the system (99 $/MWh, at least 148% higher than in the other scenarios).

We also found that there are asymmetric costs and benefits for planners to incorporate climate change. Specifically, we find that the costs of erroneously ignoring climate change in planning (that is, ignoring climate change but experiencing its impacts later) can be significant - an increase of 59 $/MWh (+147%). On the other hand, the additional costs of erroneously accounting for climate change (that is, planning for climate change but experiencing negligible climate impacts) are relatively minor - on the order of 3 $/MWh (+9%). Furthermore, we found that the additional investment and operating costs needed to avoid the LOL that occurs in scenario *Ignore CC/CC occurs* would represent around $175 for each MWh of unserved load, which is considerably lower than estimated values of the willingness of electricity consumers to pay to avoid LOL.

Table 2: Summary of results

CO_2 constraint	Scenario	Installed Capacity (GW)	Normalized cost of Energy ($/MWh)	Annual Generation (TWh)	Total Annual Cost (Billion $)	Annual Lost Load (TWh)
No CO_2 limits	Ignore CC/ no CC effects	150.4	36.8	653.9	24.1	0.0
	Plan for CC/ CC effects	202.2	40.2	672.5	27.0	0.1
	Plan for CC/ no CC effects	202.2	40.0	653.9	26.1	0.0
	Ignore CC/ CC effects	150.4	99.3	672.5	66.9	14.1
50% CO_2 reduction	Ignore CC/ no CC effects	153.9	36.8	653.9	24.1	0.0
	Plan for CC/ CC effects	209.0	40.3	672.5	27.1	0.1
	Plan for CC/ no CC effects	209.0	40.2	653.9	26.3	0.0
	Ignore CC/ CC effects	153.9	93.0	672.5	62.6	12.7
80% CO_2 reduction	Ignore CC/ no CC effects	252.9	40.9	653.9	26.7	0.0
	Plan for CC/ CC effects	297.0	44.0	672.5	29.6	0.0
	Plan for CC/ no CC effects	297.0	44.7	653.9	29.2	0.0
	Ignore CC/ CC effects	252.9	44.9	672.5	30.2	1.0

Our sensitivity analysis on CO_2 emissions policies found that fleets that achieve an 80% reduction in CO_2 emissions have operations that are less vulnerable to impacts of climate change. This finding suggests a synergy between adaptation and mitigation investment strategies. That is, climate mitigation investments in the power sector can simultaneously further climate adaptation in the power sector. This finding aligns with the results of our prior research,[37] which found that adapting to climate change shifted investments towards low-carbon power, yielding synergies with mitigation activities.

Several caveats pertain to our analysis and results. First, while our expansion optimizations accounted for the uncertainty in climate projections, they were optimized assuming

static information. All investment decisions for the planning horizon (2015–2050) are defined at the beginning of the period, using the information available at this time (e.g., the projections of climate-induced impacts). In real life, planning agents might change their decisions as they observe extreme hazards simulated in scenario *Ignore CC/CC occurs*. Our results in scenario *Ignore CC/CC occurs* could be interpreted as a "worst-case" scenario. Future work could model how planning decisions change as an agent acquires information (e.g., using a real options framework[60]).

Because we aimed to isolate first order impacts of climate change on the power grid, we assumed that future electricity demand would only differ from present values because of changes in climate conditions. Future analysis should also integrate socio-economic and technological changes with climate-induced ones. For example, electrified transport could increase total annual electricity consumption between 25% and 71% by 2050.[61] Demand for air conditioning – the main driver of the increase in LOL in our results – will also depend on socio-economic factors like affordability.[7] Expected population growth in our study region[62] would likely change load patterns and, in turn, planning and operational tradeoffs found in our results. Given the lack of empirical data that could be used to develop demand scenarios as a result of increased electrification of end-uses and population shifts, work to develop such scenarios should be the focus of future work. Also, our simulations of electricity demand did not explicitly include the impact of air humidity on electricity demand. In previous work,[14] we tested a model for demand that included air humidity as an independent driver. In such an analysis, we found only marginal improvements in model fit compared to the formulation without humidity. To improve computation efficiency, for this paper we thus used the simpler formulation without humidity. A recent study suggests humidity levels could affect residential cooling demand.[63] However, the authors found that the impact of humidity on the estimates for demand in Southeastern states was relatively lower than for states west of the Mississippi. Indeed, including humidity in the model formulation could result in lower demand estimates in some Southeastern states (like North Carolina, South

Carolina, Alabama, and Mississippi). The inclusion of humidity in the demand model is likely more critical in an analysis for other regions than for our study. Furthermore, the results of an analysis that includes humidity would likely show qualitatively similar results to the ones we present but with higher loss-of-load probability when ignoring climate impacts in the planning process.

We ignore climate change impacts on transmission and wind and solar generation. Transmission capacity is sensitive to ambient air temperature, so climate change could reduce transmission capacity.[24,64] Climate change could also affect solar and wind generation profiles,[26,30,33] which could impact our results given the substantial participation of renewables in our future fleets. However, downscaling future wind and solar resources to the hourly resolution necessary for our models is the subject of significant ongoing research and computationally costly. Future work could incorporate these factors in our modeling framework and would be particularly important for understanding the climate-induced impacts on low-carbon power systems. Finally, in this work we do not capture system vulnerabilities to worsened extreme weather events under climate change, such as hurricanes, floods, and wildfires.[65–68] Models that capture these vulnerabilities typically use robust or stochastic optimization methods, which are not computationally tractable at the scale of our system. We leave the integration of such impacts to future work.

In spite of these modeling limitations, the results presented in this study could inform planning agents in the power sector to come up with adaptation strategies to cope with climate change risks. According to our results, making present-day planning decisions that account for climate-induced effects would be substantially less costly than ignoring these risks. Other adaptation strategies not included in our analysis framework would also be important to make the grid more resilient to the impacts of climate change. For example, in our analysis we assumed that energy efficiency would remain constant at present levels. However, increasing efficiency of air conditioning could also be an important adaptation strategy. Some of these adaptation strategies – such as installing more wind and solar

power plants – would also help to mitigate future CO_2 emissions, as we found in our results under a 80% CO_2 cap. This dual benefit of these strategies (adaptation and mitigation) make them even more attractive. As planning agents look into sustainable pathways for the decarbonization of electricity generation, studies that integrate the different vulnerabilities of the power system to climate change will help decision-makers mitigate reliability and affordability challenges facing the design of the future power grid.

Acknowledgments

Funding for this work came from the National Science Foundation (NSF) as part of the Resilient Interdependent Infrastructure Processes and Systems (RIPS) program via Grant Number EFRI-1441131. This work used the Extreme Science and Engineering Discovery Environment (XSEDE),[69] which is supported by National Science Foundation grant number ACI-1548562. Specifically, it used the Bridges system,[70] which is supported by NSF award number ACI-1445606, at the Pittsburgh Supercomputing Center (PSC).

Supporting Information

Additional details of modeling framework; detailed formulation of optimization model; parameters used in the capacity expansion model; tables and figures with additional results.

References

(1) IPCC, In *Global warming of 1.5 C. An IPCC Special Report on the impacts of global warming of 1.5 C above pre industrial levels and related global greenhouse gas emission pathways, in the context of strengthening the global response to the threat of climate change,*; Masson-Delmotte, V., Zhai, P., Pörtner, H.-O., Roberts, D., Skea, J., Shukla, P. R., Pirani, A., Moufouma-Okia, W., Péan, C., Pidcock, R., Connors, S.,

Matthews, J. B. R., Chen, Y., Zhou, X., Gomis, M. I., Lonnoy, E., Maycock, T., Tignor, M., Waterfield, T., Eds.; 2018; p 32.

(2) USGCRP, In *Impacts, Risks, and Adaptation in the United States: Fourth National Climate Assessment, Volume II*; Reidmiller, D. R., Avery, C. W., Easterling, D. R., Kunkel, K. E., Lewis, K., Maycock, T. K., Stewart, B. C., Eds.; U.S. Global Change Research Program: Washington, DC, USA, 2018; p 1515.

(3) Bonneville Power Administration, BPA prepares for a changing climate. 2014; `https://www.bpa.gov/news/newsroom/Pages/BPA-prepares-for-a-changing-climate.aspx`.

(4) Tennesse Valley Authority, *Climate Change Adaptation Action Plan*; 2016.

(5) Hydro-Québec, *Sustainability Report 2018*; 2018.

(6) US Department of Energy, *Climate Change and the U.S. Energy Sector: Regional Vulnerabilities and Resilience Solutions*; 2015; p 193.

(7) Yalew, S. G.; van Vliet, M. T.; Gernaat, D. E.; Ludwig, F.; Miara, A.; Park, C.; Byers, E.; De Cian, E.; Piontek, F.; Iyer, G.; Mouratiadou, I.; Glynn, J.; Hejazi, M.; Dessens, O.; Rochedo, P.; Pietzcker, R.; Schaeffer, R.; Fujimori, S.; Dasgupta, S.; Mima, S.; da Silva, S. R.; Chaturvedi, V.; Vautard, R.; van Vuuren, D. P. Impacts of climate change on energy systems in global and regional scenarios. *Nature Energy* **2020**, *5*, 794–802.

(8) Sailor, D. J. Relating residential and commercial sector electricity loads to climate - Evaluating state level sensitivities and vulnerabilities. *Energy* **2001**, *26*, 645–657.

(9) Sailor, D. J.; Pavlova, A. A. Air conditioning market saturation and long-term response of residential cooling energy demand to climate change. *Energy* **2003**, *28*, 941–951.

(10) Franco, G.; Sanstad, A. H. Climate change and electricity demand in California. *Climatic Change* **2007**, *87*, 139–151.

(11) McFarland, J.; Zhou, Y.; Clarke, L.; Sullivan, P.; Colman, J.; Jaglom, W. S.; Colley, M.; Patel, P.; Eom, J.; Kim, S. H.; Kyle, G. P.; Schultz, P.; Venkatesh, B.; Haydel, J.; Mack, C.; Creason, J. Impacts of rising air temperatures and emissions mitigation on electricity demand and supply in the United States: a multi-model comparison. *Climatic Change* **2015**, *131*, 111–125.

(12) Dirks, J. A.; Gorrissen, W. J.; Hathaway, J. H.; Skorski, D. C.; Scott, M. J.; Pulsipher, T. C.; Huang, M.; Liu, Y.; Rice, J. S. Impacts of climate change on energy consumption and peak demand in buildings: A detailed regional approach. *Energy* **2015**, *79*, 20–32.

(13) Auffhammer, M.; Baylis, P.; Hausman, C. H. Climate change is projected to have severe impacts on the frequency and intensity of peak electricity demand across the United States. *Proceedings of the National Academy of Sciences* **2017**, *114*, 1886–1891.

(14) Ralston Fonseca, F.; Jaramillo, P.; Bergés, M.; Severnini, E. Seasonal effects of climate change on intra-day electricity demand patterns. *Climatic Change* **2019**, *33*, 1–17.

(15) Turner, S. W.; Hejazi, M.; Kim, S. H.; Clarke, L.; Edmonds, J. Climate impacts on hydropower and consequences for global electricity supply investment needs. *Energy* **2017**, *141*, 2081–2090.

(16) Kao, S. C.; Sale, M. J.; Ashfaq, M.; Uria Martinez, R.; Kaiser, D. P.; Wei, Y.; Diffenbaugh, N. S. Projecting changes in annual hydropower generation using regional runoff data: An assessment of the United States federal hydropower plants. *Energy* **2015**, *80*, 239–250.

(17) Forrest, K.; Tarroja, B.; Chiang, F.; AghaKouchak, A.; Samuelsen, S. Assessing climate

change impacts on California hydropower generation and ancillary services provision. *Climatic Change* **2018**, *151*, 395–412.

(18) Hamlet, A. F.; Lee, S. Y.; Mickelson, K. E.; Elsner, M. M. Effects of projected climate change on energy supply and demand in the Pacific Northwest and Washington State. *Climatic Change* **2010**, *102*, 103–128.

(19) Koch, H.; Vögele, S. Dynamic modelling of water demand, water availability and adaptation strategies for power plants to global change. *Ecological Economics* **2009**, *68*, 2031–2039.

(20) Koch, H.; Vögele, S.; Kaltofen, M.; Grünewald, U. Trends in water demand and water availability for power plants-scenario analyses for the German capital Berlin. *Climatic Change* **2012**, *110*, 879–899.

(21) Bartos, M. D.; Chester, M. V. Impacts of climate change on electric power supply in the Western United States. *Nature Climate Change* **2015**, *5*, 748–752.

(22) Van Vliet, M. T.; Yearsley, J. R.; Ludwig, F.; Vögele, S.; Lettenmaier, D. P.; Kabat, P. Vulnerability of US and European electricity supply to climate change. *Nature Climate Change* **2012**, *2*, 676–681.

(23) Tobin, I.; Greuell, W.; Jerez, S.; Ludwig, F.; Vautard, R.; Van Vliet, M. T.; Breón, F. M. Vulnerabilities and resilience of European power generation to 1.5 c, 2 c and 3 c warming. *Environmental Research Letters* **2018**, *13*, 044024.

(24) Bartos, M.; Chester, M.; Johnson, N.; Gorman, B.; Eisenberg, D.; Linkov, I.; Bates, M. Impacts of rising air temperatures on electric transmission ampacity and peak electricity load in the United States. *Environmental Research Letters* **2016**, *11*, 114008.

(25) Bloomfield, H.; Brayshaw, D.; Troccoli, A.; Goodess, C.; De Felice, M.; Dubus, L.; Bett, P.; Saint-Drenan, Y.-M. Quantifying the sensitivity of european power systems to

energy scenarios and climate change projections. *Renewable Energy* **2021**, *164*, 1062–1075.

(26) Carreño, I. L.; Craig, M. T.; Rossol, M.; Ashfaq, M.; Batibeniz, F.; Haupt, S. E.; Draxl, C.; Hodge, B.-M.; Brancucci, C. Potential impacts of climate change on wind and solar electricity generation in Texas. *Climatic Change* **2020**, *163*, 745–766.

(27) Kimmell, T. A.; Veil, J. A. *Impact of drought on U.S. steam electric power plant cooling water intakes and related water resource management issues.*; 2009.

(28) EDF cuts output at St. Alban nuclear power plant as France boils. `https://af.reuters.com/article/commoditiesNews/idAFL8N24O5NM`.

(29) Flessner, D. Hot weather pushes TVA power peak to highest August in seven years. `https://www.timesfreepress.com/news/breakingnews/story/2019/aug/14/hot-weather-pushes-tva-power-peak-highest-august-seven-years/501133/`.

(30) Craig, M. T.; Cohen, S.; Macknick, J.; Draxl, C.; Guerra, O. J.; Sengupta, M.; Haupt, S. E.; Hodge, B. M.; Brancucci, C. A review of the potential impacts of climate change on bulk power system planning and operations in the United States. *Renewable and Sustainable Energy Reviews* **2018**, *98*, 255–267.

(31) Payet-Burin, R.; Bertoni, F.; Davidsen, C.; Bauer-Gottwein, P. Optimization of regional water - power systems under cooling constraints and climate change. *Energy* **2018**, *155*, 484–494.

(32) Turner, S. W.; Voisin, N.; Fazio, J.; Hua, D.; Jourabchi, M. Compound climate events transform electrical power shortfall risk in the Pacific Northwest. *Nature Communications* **2019**, *10*, 8.

(33) Craig, M. T.; Carreño, I. L.; Rossol, M.; Hodge, B.-M.; Brancucci, C. Effects on power

611 system operations of potential changes in wind and solar generation potential under
612 climate change. *Environmental Research Letters* **2019**, *14*, 034014.

613 (34) Peter, J. How does climate change affect electricity system planning and optimal allo-
614 cation of variable renewable energy? *Applied Energy* **2019**, *252*, 113397.

615 (35) Schlott, M.; Kies, A.; Brown, T.; Schramm, S.; Greiner, M. The impact of climate
616 change on a cost-optimal highly renewable European electricity network. *Applied Energy*
617 **2018**, *230*, 1645–1659.

618 (36) Miara, A.; Cohen, S. M.; Macknick, J.; Vörösmarty, C. J.; Corsi, F.; Sun, Y.; Tid-
619 well, V. C.; Newmark, R.; Fekete, B. M. Climate-Water Adaptation for Future US
620 Electricity Infrastructure. *Environmental Science and Technology* **2019**, *53*, 14029–
621 14040.

622 (37) Ralston Fonseca, F.; Craig, M. T.; Jaramillo, P.; Berges, M.; Severnini, E.; Loew, A.;
623 Zhai, H.; Cheng, Y.; Nijssen, B.; Voisin, N.; Yearsley, J. Effects of climate change on
624 capacity expansion decisions of an electricity generation fleet in the Southeast U.S.
625 *Environmental Science and Technology* **2021**, *17*.

626 (38) Taylor, K. E.; Stouffer, R. J.; Meehl, G. A. An overview of CMIP5 and the experiment
627 design. *Bulletin of the American Meteorological Society* **2012**, *93*, 485–498.

628 (39) Abatzoglou, J. T.; Brown, T. J. A comparison of statistical downscaling methods suited
629 for wildfire applications. *International Journal of Climatology* **2012**, *32*, 772–780.

630 (40) Liang, X.; Lettenmaier, D. P.; Wood, E. F.; Burges, S. J. A simple hydrologically based
631 model of land surface water and energy fluxes for general circulation models. *Journal*
632 *of Geophysical Research* **1994**, *99*, 14415.

633 (41) Li, H.; Wigmosta, M. S.; Wu, H.; Huang, M.; Ke, Y.; Coleman, A. M.; Leung, L. R. A

Physically Based Runoff Routing Model for Land Surface and Earth System Models. *Journal of Hydrometeorology* **2013**, *14*, 808–828.

(42) Voisin, N.; Li, H.; Ward, D.; Huang, M.; Wigmosta, M.; Leung, L. R. On an improved sub-regional water resources management representation for integration into earth system models. *Hydrol. Earth Syst. Sci* **2013**, *17*, 3605–3622.

(43) Voisin, N.; Hejazi, M. I.; Leung, L. R.; Liu, L.; Huang, M.; Li, H.-Y.; Tesfa, T. Effects of spatially distributed sectoral water management on the redistribution of water resources in an integrated water model. *Water Resources Research* **2017**, *53*, 4253–4270.

(44) Niemeyer, R. J.; Cheng, Y.; Mao, Y.; Yearsley, J. R.; Nijssen, B. A Thermally Stratified Reservoir Module for Large-Scale Distributed Stream Temperature Models With Application in the Tennessee River Basin. *Water Resources Research* **2018**, *54*, 8103–8119.

(45) Yearsley, J. R. A semi-Lagrangian water temperature model for advection-dominated river systems. *Water Resources Research* **2009**, *45*.

(46) Loew, A.; Jaramillo, P.; Zhai, H.; Ali, R.; Nijssen, B.; Cheng, Y.; Klima, K. Fossil fuel–fired power plant operations under a changing climate. *Climatic Change* **2020**, 1–14.

(47) Carnegie Mellon University, Integrated Environmental Control Model (IECM) Version 11.2. 2018; `http://cmu.edu/epp/iecm/index.html`.

(48) Zhai, H.; Rubin, E. S.; Versteeg, P. L. Water use at pulverized coal power plants with postcombustion carbon capture and storage. *Environmental Science and Technology* **2011**, *45*, 2479–2485.

(49) US Environmental Protection Agency (EPA), Documentation for EPA's Power Sector Modeling Platform v6: Using the Integrated Planning Model. 2018;

https://www.epa.gov/sites/production/files/2018-05/documents/epa{_}platform{_}v6{_}documentation{_}-{_}all{_}chapters{_}v15{_}may{_}31{_}10-30{_}am.pdf.

(50) Abatzoglou, J. T. Development of gridded surface meteorological data for ecological applications and modelling. *International Journal of Climatology* **2013**, *33*, 121–131.

(51) Bennett, A.; Hamman, J.; Nijssen, B. MetSim: A Python package for estimation and disaggregation of meteorological data. *Journal of Open Source Software* **2020**, *5*, 2042.

(52) Voisin, N.; Kintner-Meyer, M.; Skaggs, R.; Nguyen, T.; Wu, D.; Dirks, J.; Xie, Y.; Hejazi, M. Vulnerability of the US western electric grid to hydro-climatological conditions: How bad can it get? *Energy* **2016**, *115*, 1–12.

(53) Haarsma, R. J.; Roberts, M. J.; Vidale, P. L.; Catherine, A.; Bellucci, A.; Bao, Q.; Chang, P.; Corti, S.; Fučkar, N. S.; Guemas, V.; Von Hardenberg, J.; Hazeleger, W.; Kodama, C.; Koenigk, T.; Leung, L. R.; Lu, J.; Luo, J. J.; Mao, J.; Mizielinski, M. S.; Mizuta, R.; Nobre, P.; Satoh, M.; Scoccimarro, E.; Semmler, T.; Small, J.; Von Storch, J. S. High Resolution Model Intercomparison Project (HighResMIP v1.0) for CMIP6. *Geoscientific Model Development* **2016**, *9*, 4185–4208.

(54) US National Renewable Energy Laboratory, Solar Power Data for Integration Studies. 2010; https://www.nrel.gov/grid/solar-power-data.html.

(55) Draxl, C.; Clifton, A.; Hodge, B. M.; McCaa, J. The Wind Integration National Dataset (WIND) Toolkit. *Applied Energy* **2015**, *151*, 355–366.

(56) Craig, M. T.; Jaramillo, P.; Hodge, B. M. Carbon dioxide emissions effects of grid-scale electricity storage in a decarbonizing power system. *Environmental Research Letters* **2018**, *13*, 014004.

(57) London Economics International LLC, *Estimating the value of lost load*; 2013; pp 3–76.

(58) US Bureau of Labor Statistics, CPI Inflation Calculator. https://www.bls.gov/data/inflation{_}calculator.htm.

(59) Milligan, M. *Methods to Model and Calculate Capacity Contributions of Variable Generation for Resource Adequacy Planning*; 2011.

(60) Guthrie, G. Real options analysis of climate-change adaptation: investment flexibility and extreme weather events. *Climatic Change* **2019**, *156*, 231–253.

(61) Mai, T.; Jadun, P.; Logan, J.; Mcmillan, C.; Muratori, M.; Steinberg, D.; Vimmerstedt, L.; Jones, R.; Haley, B.; Nelson, B. *Electrification Futures Study: Scenarios of Electric Technology Adoption and Power Consumption for the United States*; 2018.

(62) University of Virginia Weldon Cooper Center - Demographics Research Group, National Population Projections. 2018; https://demographics.coopercenter.org/national-population-projections.

(63) Maia-Silva, D.; Kumar, R.; Nateghi, R. The critical role of humidity in modeling summer electricity demand across the United States. *Nature Communications* **2020**, *11*.

(64) Sathaye, J. A.; Dale, L. L.; Larsen, P. H.; Fitts, G. A.; Koy, K.; Lewis, S. M.; de Lucena, A. F. P. Estimating impacts of warming temperatures on California's electricity system. *Global Environmental Change* **2013**, *23*, 499–511.

(65) Dumas, M.; Kc, B.; Cunliff, C. I. *Extreme Weather and Climate Vulnerabilities of the Electric Grid: A Summary of Environmental Sensitivity Quantification Methods*; 2019.

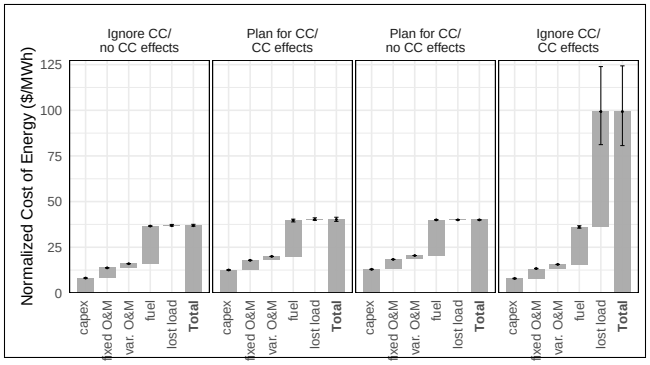
(66) Staid, A.; Guikema, S. D.; Nateghi, R.; Quiring, S. M.; Gao, M. Z. Simulation of tropical cyclone impacts to the U.S. power system under climate change scenarios. *Climatic Change* **2014**, *127*, 535–546.

(67) Panteli, M.; Pickering, C.; Wilkinson, S.; Dawson, R.; Mancarella, P. Power System

Resilience to Extreme Weather: Fragility Modeling, Probabilistic Impact Assessment, and Adaptation Measures. *IEEE Transactions on Power Systems* **2017**, *32*, 3747–3757.

(68) Bennett, J. A.; Trevisan, C. N.; DeCarolis, J. F.; Ortiz-García, C.; Pérez-Lugo, M.; Etienne, B. T.; Clarens, A. F. Extending energy system modelling to include extreme weather risks and application to hurricane events in Puerto Rico. *Nature Energy* **2021**, *6*, 240–249.

(69) Towns, J.; Cockerill, T.; Dahan, M.; Foster, I.; Gaither, K.; Grimshaw, A.; Hazlewood, V.; Lathrop, S.; Lifka, D.; Peterson, G. D.; Roskies, R.; Scott, J. R.; Wilkens-Diehr, N. XSEDE: Accelerating Scientific Discovery. *Computing in Science & Engineering* **2014**, *16*, 62–74.

(70) Nystrom, N. A.; Levine, M. J.; Roskies, R. Z.; Scott, J. R. Bridges: A Uniquely Flexible HPC Resource for New Communities and Data Analytics. Proceedings of the 2015 XSEDE Conference: Scientific Advancements Enabled by Enhanced Cyberinfrastructure. New York, NY, USA, 2015; pp 30:1–30:8.

Graphical TOC Entry