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

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Abstract

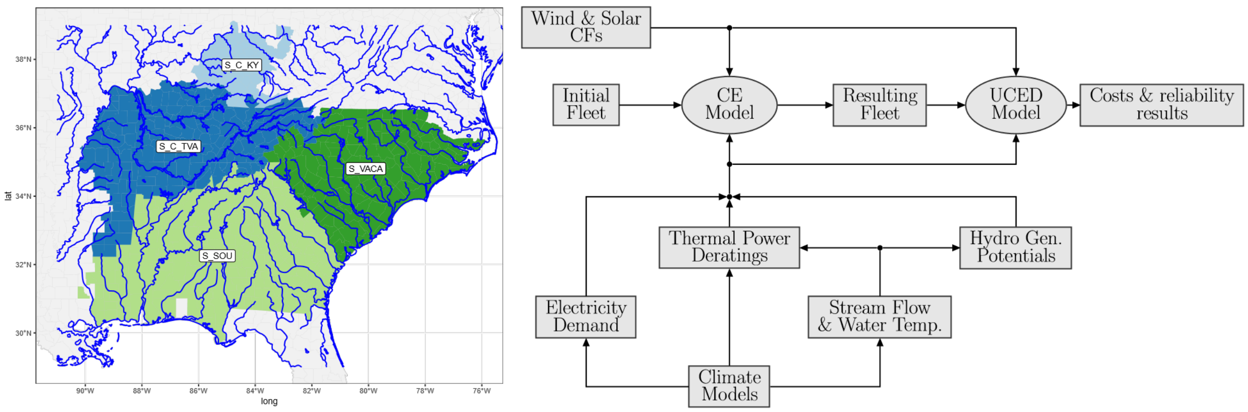
Electricity grid planners design the system in order to supply electricity to end users reliably and affordably. Climate change threatens both objectives through potentially compounding supplyand demand-side climate-induced impacts. Uncertainty surrounds each of these future potential impacts. Given 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.

1 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 [30]. Meteorological variability, climatic extremes, and droughts will also likely increase [75]. Utilities have already started discussing adaptation strategies to address potential climate impacts on their grids [11, 62, 29], which will manifest in several ways [71, 80]. On the demand side, warming temperatures will likely result in changes in electricity consumption used for ambient heating and cooling [57, 56, 25, 44, 19, 3, 55]. These changes could result in increased total consumption and peak electricity demand. On the supply side, changes in streamflow could affect hydropower generation [66, 31, 24, 28]. Also, decreased water availability, and increased water and air temperatures could reduce the capacity and efficiency of thermal units [33, 34, 7, 76, 63]. Climate change could also affect wind and solar resources, transmission assets, and other technologies essential to a zero-carbon system [6, 10, 40]. Recent events in the US and Europe have already revealed the vulnerabilities of the power system to weather extremes [32, 21, 23].

Given these aforementioned risks, a growing body of literature has analyzed how climate change might affect electric power systems [16]. Many studies have focused on impacts to individual components of the power system, such as electricity demand [44, 3, 55] or generation capacity [34, 7, 76]. 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 [51, 65, 17, 10]. 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 [52, 59, 45] 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 [52]. 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 this study, we fill this gap and investigate several 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 plan for climate change, what are the excess costs if we do not include climate change impacts? 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 [63] by considering the same ensemble of climate models, emission scenarios, 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 [61, 2] within a chain of different models to simulate synchronous climate-induced impacts on hourly electricity demand [55], daily river flows and water temperatures [37, 36, 77, 79, 48, 81], hydropower potential, and capacity deratings for thermoelectric power plants [38, 12, 82]. We integrated these impacts into a capacity expansion (CE) model [54] to create future generator fleets, then fed these impacts and fleets into a unit commitment and economic dispatch (UCED) model to simulate power system operations. By controlling for whether planning and/or operations account for climate change, we examine the trade-offs in planning and operations under climate change.



(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)

2 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*) we determined generator fleets by 2050 using the CE model ([54]) under two climate change scenarios: with and without climate change impacts. Additionally, we simulated fleet expansion under three CO_2 emission policies: no limits, 50% reduction, and 80% reduction (see Section 1.2 in SI). In the second stage (*Grid operation stage*), these generator fleets served as input into the UCED model under two scenarios: a scenario in which climate change impacts in 2050 were not included, and another in which we simulated climate-induced impacts under RCP 4.5 conditions. By taking all combinations of the two pairs of scenarios included in the capacity expansion and UCED models, we simulated four different scenarios (Table 1) for each CO_2 emission policy. 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).

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)

2.1 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 [75]. To better represent spatial differences in SERC, we used the four subregions defined in EPA's Integrated Planning Model [73].

2.2 Climate Simulations

To represent historical weather conditions, we used weather data from the University of Idaho Gridded Surface Meteorological Data (gridMET) dataset [1] for the years 1979 – 2015. This dataset combines desirable spatial attributes of gridded climate data from the PRISM dataset [53, 18] with desirable temporal attributes from the regional reanalysis dataset NLDAS-2 [47] to derive a high-resolution (1/24th degree, ~4 km) gridded dataset of daily surface meteorological variables. We then disaggregated the daily data to hourly values using METSIM (Meteorology Simulator) [9].

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) [61], spatially downscaled using the Multivariate

Adaptive Constructed Analogs (MACA) method [2]. 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.

2.3 Electricity demand

We used an econometric model to estimate the projections of SERC's electricity hourly demand in future years under different climate change scenarios [55]. To fit this model, we used historical hourly electricity demand data for the four SERC regions from the Federal Energy Regulatory Commission (FERC) Form 714 [22] for the years 2006–2015. We also used historical weather data from the gridMET dataset [1]. After defining the parameters of the econometric model, 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. Additionally, 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 backtrack 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. 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. We leave such analyses to future research and discuss the implications of our assumption in the Discussion.

2.4 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 [37], to simulate runoff. Second, the runoff was used as an input into a river routing model, the Model for Scale Adaptive River Transport (MOSART) [36], dynamically coupled to a spatially distributed water management model (WM) [77, 79], 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) [81], coupled with a two-layer reservoir thermal stratification module [48]. We ran these models at a grid resolution of 1/8 degree (~ 12 km) using the climate forcing data from twenty different GCMs from CMIP5 [61], spatially downscaled using the MACA method [2]. We used the output from twenty GCMs for the year 2050.

2.5 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 [12, 38]. The IECM outputs plant performance characteristics and costs for different combinations of power plant technologies and cooling systems. 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. This way we could map local hourly weather and stream conditions simulated by the GCMs to operating conditions for thermoelectric power plants.

For each type of cooling system, the response curves use the more significant ambient variables [38]. For once-through system the ambient variables are water intake temperature and air temperature. For recirculating cooling, the ambient variables are air temperature and air humidity.

For dry-cooling systems, the weather variables are air temperature and air pressure. 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 [38].

For existing thermal power plants with once-through cooling, we also modeled how the water discharged from the power plants affects stream temperatures using a mass balance equation. We used this estimate to simulate the maximum available capacity from once-through power plants that would not cause water temperatures downstream of the power plant to rise above a certain threshold value. Water quality standards vary by state, but they typically require surface water temperature to remain under 32°C [42]. We used this threshold value in our study. Because water withdrawal rates of recirculating cooling are estimated as 3% of the ones from once-through [41], we assumed that recirculating cooling would not be impacted by these constraints. More details about the simulation of thermal deratings are available in the SI.

2.6 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. We assumed that the potential energy available at each hydropower plant is proportional to the regulated stream flow simulated by hydrological models at the plant's location [78]. 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. More details about the simulation of hydropower potentials are available in the SI.

2.7 Wind and solar generation

We estimated inputs described thus far - demand, thermal deratings, and hydropower generation from the same ensemble of climate models. Forecasting wind and solar resources under climate change remains a significant challenge, particularly at an hourly resolution used in our modeling framework. New initiatives, e.g. High Resolution MIP [27], are beginning to release downscaled wind and solar resource data, but data released thus far is only for surface wind speeds at 3-hourly resolution. Other research has used numerical weather prediction models, e.g. the Weather Research and Forecasting model [40], to downscale wind and solar resources, 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 [16].

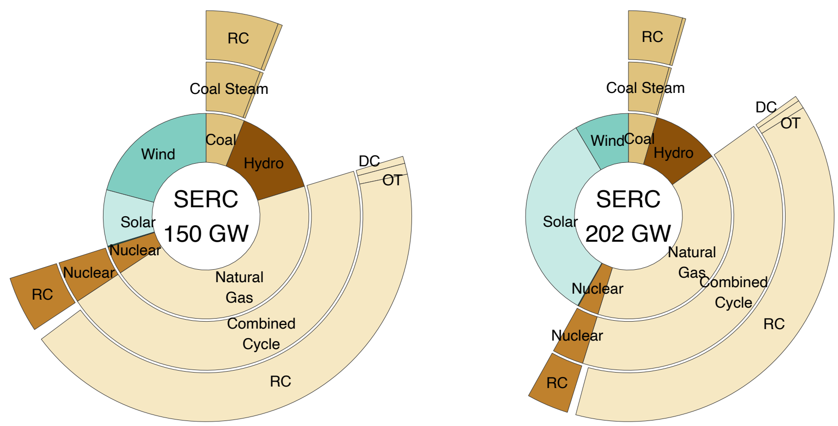
Given these challenges, we capture spatial and temporal variability in output among wind and solar farms using simulated wind and solar generation profiles from the U.S. National Renewable Energy Laboratory (NREL) [74, 20]. These wind and solar generation databases provide simulated generation profiles for hypothetical plants in the SERC area at 5-minute increments, for 2007–2012 and 2006, respectively. We used 2009 wind generation data, since the overall simulated capacity factor in this year was closer to the average over the complete data set. We aggregated generation data to hourly increments by calculating the average generation values for all time steps in each hour. We discuss the implications of using historic wind and solar data in the Discussion.

Average capacity factors for hypothetical individual wind and solar sites in SERC in the NREL dataset ranged from 17%–55% and 12%–19%, respectively (see section 1.5 in SI). We assigned the generation profiles of these individual sites to the wind and solar power plants in our existing generator fleet in order of decreasing capacity factor, assuming existing projects tap the greatest available resources. Finally, because we did not account for transmission within SERC in the power system operations model, each existing wind and solar unit varied only by capacity and hourly generation profile within each subregion. To improve the computational efficiency of the model, we thus combined wind and solar units into single equivalent wind and solar units by summing up their capacities and hourly generation profiles. 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.

2.8 Capacity expansion scenarios

The fleet configurations in 2050 used in this study were determined in a separate study [54] 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 and hourly generation of new and existing 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 [54]). The fleet configurations were determined using the same ensemble of climate models and emission scenarios used to simulate climate-induced effects on supply and demand used in this study. In each CO_2 emission scenario (no limits, 50% reduction, and 80% reduction), the CE model optimized two configurations of the generator fleet in 2050 in this study.

The first fleet (Figure 2a) was created with no effects of climate change on supply and demand. Electricity demand was simulated using historical climate data. Hydro generation potentials were equal to historical averages, and we included no climate-induced capacity deratings for thermal power plants. The second fleet (Figure 2b) was created including the effects of climate change on supply and demand under RCP 4.5 by 2050 described previously. Both configurations were created by a capacity expansion model integrated within our modeling framework. This resulted in six different fleets (see Figure S3 in SI). A detailed description of the capacity expansion model is available in Ralston Fonseca et al. [54].



(a) Ignore CC (b) Plan for CC

Figure 2: Configurations of the generator fleet in 2050 described in Ralston Fonseca et al. [54] (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.

2.9 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 [15, 17]. 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. In our grid operation scenarios under climate change, 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. This resulted in twenty different dispatch simulations in each scenario. This way, our results represented the inherent uncertainties in the climate simulations.

We repeated a similar approach in the scenarios of grid operation 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. For more details, see the SI.

2.10 Loss of load

To estimate potential impacts of climate change on reliability and cost, we quantified loss of load (LOL) events using the UCED model. The results from the UCED indicate any unserved electricity in the supply/demand equation (see section 1.9 in SI).

We quantified risk of LOL using the loss of load probability (LoLP). To compute the LoLP in our simulations, we counted the number of hours in each dispatch simulation that any type of loss of load event occurred. Then we divided this number by the total number of hours being simulated.

We quantified cost of these outages using the value of lost load (VOLL). Estimating values of lost load is an important and ongoing topic of study in energy economics [50]. Studies usually rely on one of three ways to estimate the value of lost load [35]: consumer surveys [8, 5, 60, 4]; cost estimates from previous supply outages [14]; and estimates of macroeconomic production functions [35, 13, 39]. Previous studies have found a wide range of values of lost load in different regions, from 5,000 $/MWh to 45,000 $/MWh [39]. This variability is due to methodological differences and specific characteristics of the regions analyzed.

The VOLL used in this study was based on values calculated for the Electric Reliability Council of Texas (ERCOT) [39]. ERCOT values (in 2012 USD) were 110 $/MWh for residential consumers and 5,679 $/MWh for Commercial & Industrial (C&I) consumers. We updated these values to 2015 currency [69] and combined them into a single system-wide value using shares of electricity consumption by sector reported by the US Energy Information Administration (EIA) [72]. Then, we adapted this system-wide value to the southeast U.S. using the ratio between GDP per capita in Texas and GDP per capita in the SERC states [68, 70]. For more details about LOL, LoLP, and VOLL, please see the SI.

2.11 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 the 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 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 cost of loss of load. We computed total cost of loss of load (in $/year) in each annual simulation by summing up all values of unfulfilled electricity demand and multiplying it by the value of lost load (3,018 $/MWh). More information about the other parameters in this calculation is available in the SI.

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

We also estimated the implied cost of avoiding the potential load loss in the scenario *Ignore CC/CC effects*. To estimate this cost, we computed the difference in annual investment and operating expenses in the scenarios *Plan for CC/CC effects* (*cost*) and *Ignore CC/CC effects* (*cost'*). Then we divided this monetary value by the difference in loss of load in scenarios scenarios *Plan for CC/CC effects* (*LoL*) and *Ignore CC/CC effects* (*LoL'*). This value can then be compared to the value of lost load (3,018 $/MWh).

$$\text{Implied Cost [\$/MWh]} \;=\frac{\sum_{cost\in \mathrm{C}\setminus \mathrm{LoL}} cost - \sum_{cost'\in \mathrm{C}\setminus \mathrm{LoL}} cost' \text{ [\$/year]}}{\mathrm{LOL} \;-\; \mathrm{LOL}' \text{ [MWh/year]}}$$

3 Results

Figure 3 compares the normalized cost of energy (in $/MWh) of the four scenarios analyzed. This metric takes into consideration all costs from different technologies and allows for a consistent comparison across the different scenarios and generator fleets. To compute the normalized cost of energy, we summed up all annualized fixed and variable costs and divided by the total electricity demand in each scenario. The normalized cost of energy in each scenario consists of five components: capital expenditures (capex) costs, fixed operation and maintenance (fixed O&M) costs, variable O&M costs, fuel costs, and total cost of loss of load. To compute the total cost of lost load, we used a value of lost load (i.e., consumer's average willingness to pay to avoid electricity curtailments) of 3,018 $/MWh (in 2015 USD) (see Methods).

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 normalized cost of energy was 36.8 $/MWh (*Ignore CC/no CC effects*) and 99.3 $/MWh (*Ignore CC/CC effects*) (2015 USD). In the scenarios where planning did account for climate-induced risks (*Plan for*

CC/CC effects and *Plan for CC/no CC effects*), the normalized cost of energy was 40 \$/MWh. Planning for climate change resulted in capex costs of approximately 12.7 \$/MWh, roughly 60% higher than when ignoring climate change (8 \$/MWh). 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*, variable costs (fuel + variable O&M) are approximately 19.5 \$/MWh. In scenarios *Ignore CC/no CC effects* and *Ignore CC/CC effects* variable costs are approximately 20.5 \$/MWh. The total cost of lost load dominates the normalized cost of energy in scenario *Ignore CC/CC effects* (Figure 3). In this scenario, the total cost of lost load accounts for 64% of the normalized cost of energy, which makes this scenario the costliest.

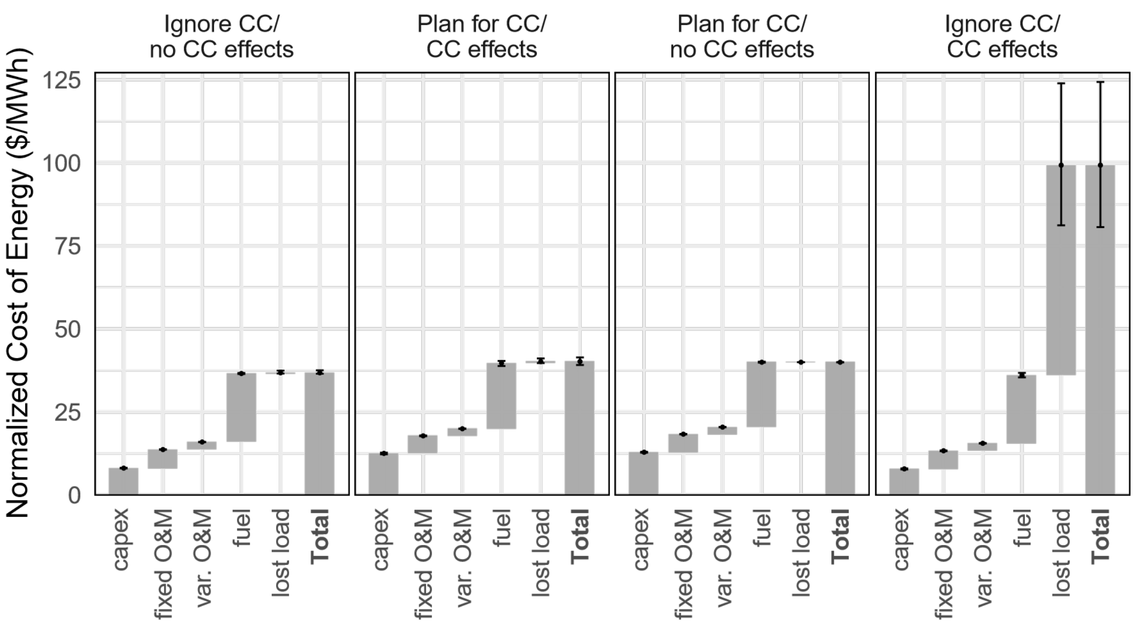


Figure 3: Comparison of normalized costs of energy in 2050 in the four scenarios. The values are the average of the simulations using data from twenty different GCMs. Error bars represent the 90% uncertainty range of each component over the twenty GCM simulations.

Given the importance of the total cost of lost load in our results, we further investigate the value of lost load. We performed additional analysis to contextualize the implications of the value of loss of load in our scenarios. Specifically, we estimated the implied cost of avoiding the large amount of load loss in the scenario *Ignore CC/CC effects* (see Methods). This way we could compare it to the estimated values in the literature. According to our results, the cost of avoiding the amount of load loss in scenario *Ignore CC/CC effects* would be approximately 175 $/MWh (6% of the value of lost load used in Figure 3). This result suggests that the cost (in $/MWh) of planning for climate change and thus avoiding lost load is substantially lower than the values of the willingness of consumers to pay to avoid a period without electricity currently used in the literature.

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.

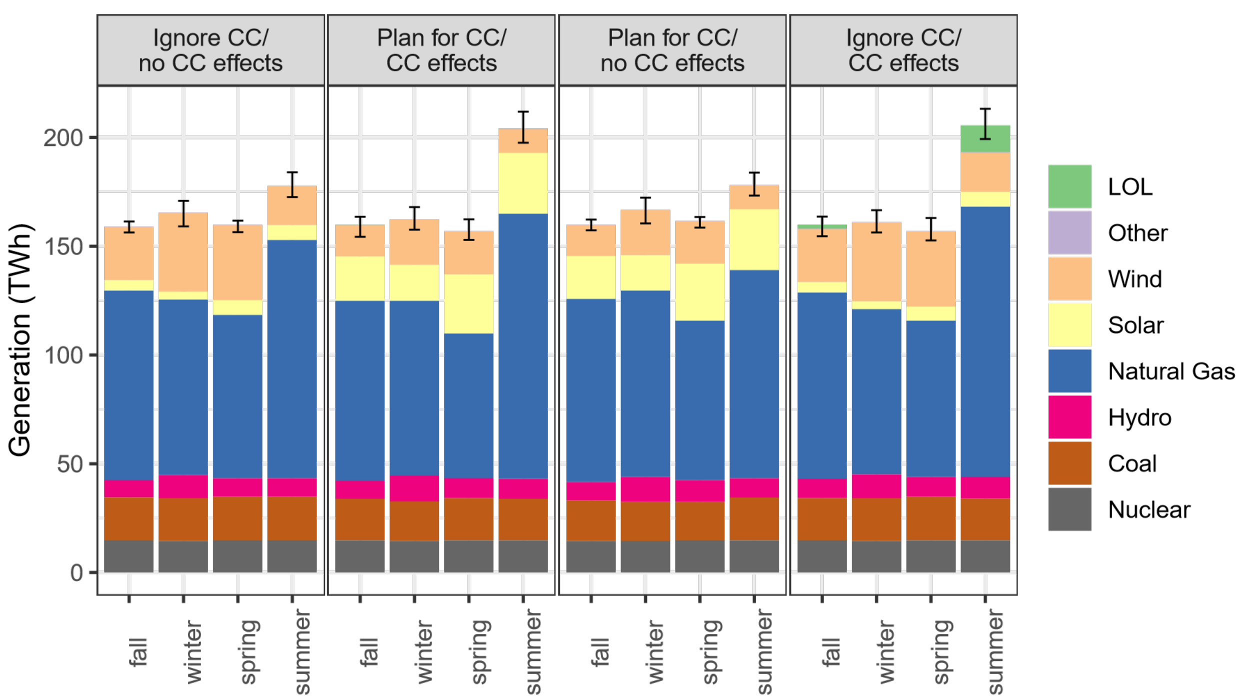


Figure 4: Comparison of the generation by source in each season and scenario. Generation values are averages over the twenty annual simulations in each scenario. Error bars represent the 90% uncertainty range of the total generation over the twenty GCM simulations.

The generation profiles in the summer are of particular interest. 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 were not able to operate at full capacity during summertime under RCP 4.5 conditions, there was a steep increase in the occurrence of loss of load events. In scenario *Ignore CC/CC effects*, the system fails to deliver 12 TWh of the summertime electricity demand (average of the UCED simulations for 2050 using data from twenty GCMs).

3.1 Loss of load probability

Figure 5a shows the distribution of loss of load probability (LoLP) in each of the four scenarios. LoLP quantifies the expected number of hours in the year when a loss of load event of any magnitude happened 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. This aligns with negligible lost load observed in those scenarios (Figure 5a). 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 the scenario where the capacity expansion model did not account for climate induced constraints, but climate change impacts were included in the 2050 operations stage, 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 in this last scenario is due to two interrelated climate-induced constraints that were not considered in the planning stage: the increase in electricity demand related to changes in climate conditions, and the potential reduction in thermal capacity in summertime.

Figure 5b compares the kernel densities of the loss of load 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 loss of load events. The density plots for scenarios *Ignore CC/no CC effects* and *Plan for CC/CC effects* present similar distributions of loss of load events. Both distributions have low probabilities of any type of shortage event. The average loss of load value in these two scenarios is approximately 3.8 GW and 4.5 GW, respectively. On the other hand, *Ignore CC/CC effects* shows a wide range of possible values of load loss. The average load loss value is approximately 14 GW. However, there is a 2% probability that simulated load losses in this scenario could surpass 23 GW (17% of the average peak demand value in this scenario).

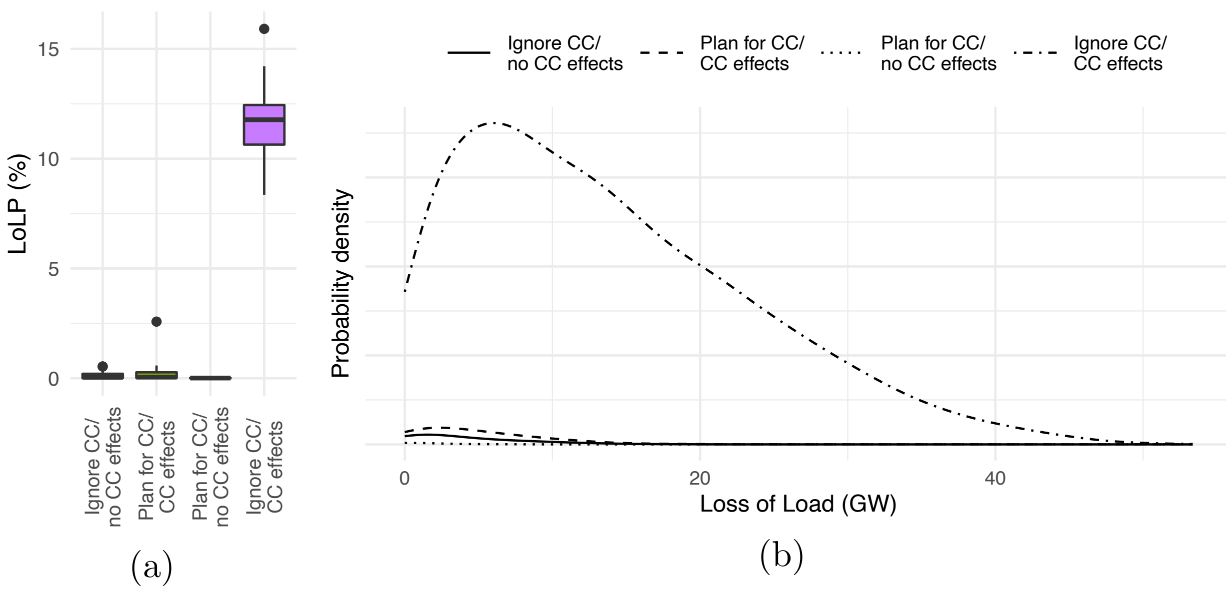


Figure 5: (a) Comparison of the loss of load probability (LoLP) in the four scenarios simulated. These values represent the expected number of hours in the year when a loss of load event of any magnitude happened in our simulations. The boxplots in each scenario were compiled by simulating 8760 hours 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 loss of load (LoL) in the four scenarios simulated. Areas under the four curves are scaled in order to represent the different values of the overall probabilities of loss of load in each scenario.

3.2 Drivers of loss of load

Under-investment in capacity drives high values of lost load in 2050 in scenario *Ignore CC/CC effects*. To quantify the drivers of lost load, we used the following heuristic: load losses are driven by thermal deratings first and under-investment in capacity second. Figure 6a shows the breakdown of the average lost load (in GW) that result from thermal deratings and from capacity shortfalls as a result of under-investments in capacity. Capacity shortfalls account, on average, for approximately 70% of the amount of lost load. Thermal deratings account for approximately 30%. The error bars represent the range of variability of each component over the twenty GCMs simulated.

While under-investment in capacity accounts for a larger percentage of the lost load in 2050 in scenario *Ignore CC/CC effects*, loss of load events driven by thermal derating happen more frequently than the ones driven by capacity shortfall. Figure 6b shows the joint density plot of the two components. The horizontal axis represents the value of lost load caused by thermal deratings, while the vertical axis shows the lost load caused by capacity shortfalls that result from under-investments in capacity. 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. This figure highlights that capacity shortfalls that result from under-investments in capacity are responsible for larger loss of load events that happen infrequently. Thermal deratings, on the other hand, lead to smaller but more frequent loss of load events. The mode of the distributions is located at a point where thermal deratings account for approximately 3 GW of lost load while capacity shortfalls are close to zero. Load losses driven by thermal deratings have a maximum value of approximately 7 GW. Simulated load losses 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 shortages in installed capacity.

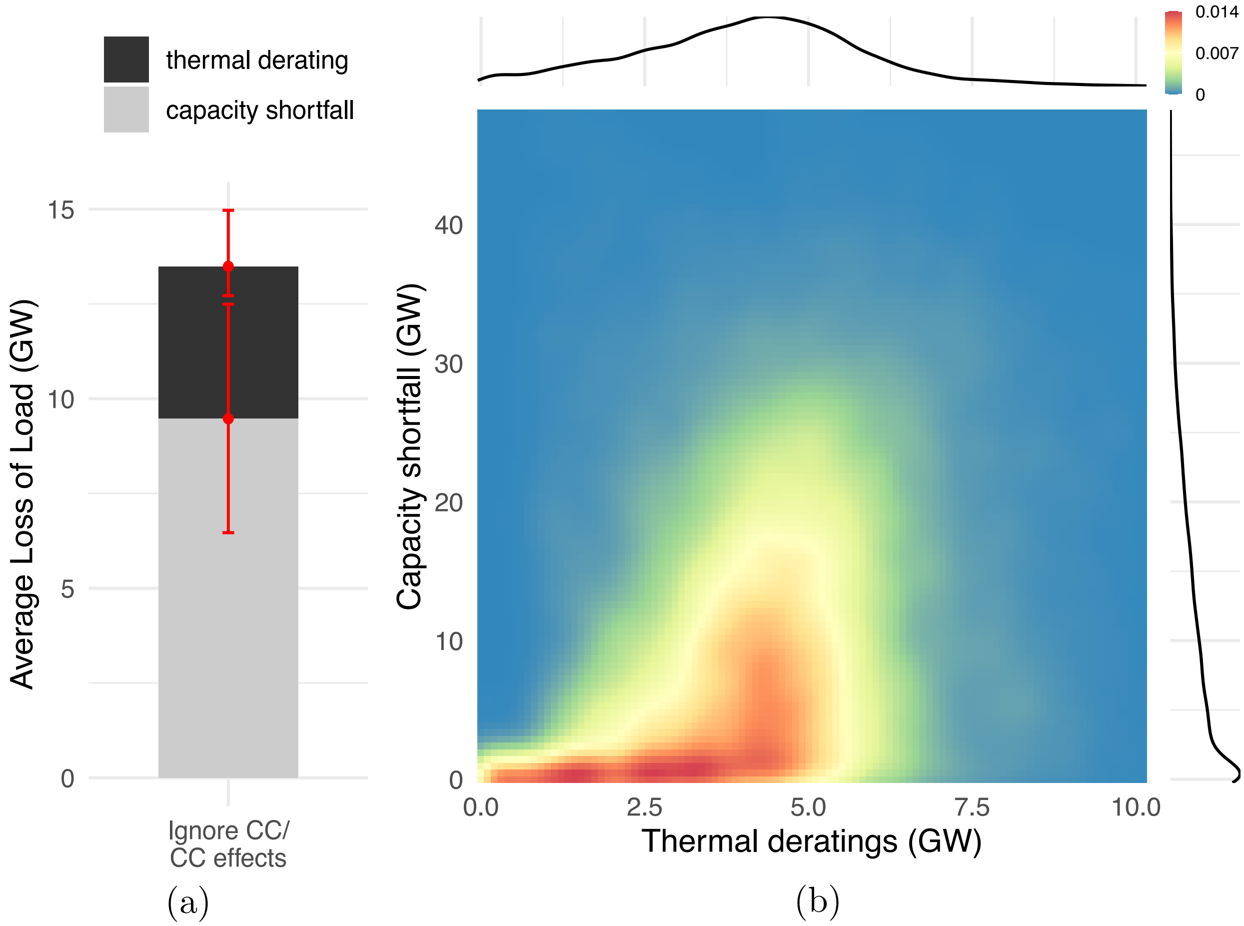


Figure 6: Decomposition of the loss of load values in scenario *Ignore CC/CC occurs*. The thermal derating component corresponds to loss of load events that occurred because of the deratings of thermal generators. The capacity shortfall component corresponds to those loss of loads caused by the lack 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.

3.3 Planning with CO2 emission targets

We also performed fleet expansion simulations imposing 50% and 80% reduction in CO_2 emissions by 2050 [54] (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 deployments of solar and wind in order to meet the emissions target. Cost and reliability results with this CO_2 emission constraint in each scenario 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 [54] from the ones planned without CO_2 limits (see Figure S3 in SI). In the scenarios with 80% reduction, 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 lost load 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 lost load 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).

4 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 (or equivalently, 0.03%) [46]. For the fleets planned without CO_2 constraints, the results from the sce narios *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 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).

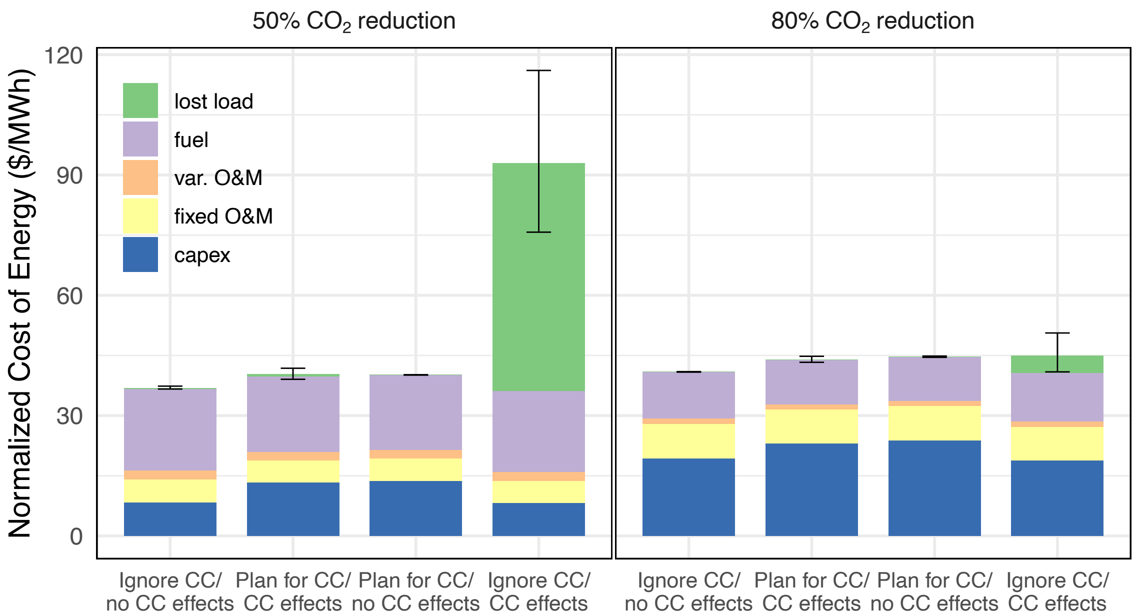


Figure 7: Comparison of normalized costs of energy in 2050 of the fleets planned with 50% and 80% reductions in CO_2 emissions (compared to 2015). The values are the average of the simulations using data from twenty different GCMs. Error bars represent the 90% uncertainty range of the total cost over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

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 lost load 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 loss of load.

Table 2: Summary of results

CO_2 constraint	Scenario	Installed Capacity (GW)	Normalized cost of Energy ($/MWh)	Annual Demand (TWh)	Annual Lost Load (TWh)
No CO_2 limits	Ignore CC/no CC effects	150.4	36.8	653.9	0.0
	Plan for CC/CC effects	202.2	40.2	672.5	0.1
	Plan for CC/no CC effects	202.2	40.0	653.9	0.0
	Ignore CC/CC effects	150.4	99.3	672.5	14.1
50% CO_2 reduction	Ignore CC/no CC effects	153.9	36.8	653.9	0.0
	Plan for CC/CC effects	209.0	40.3	672.5	0.1
	Plan for CC/no CC effects	209.0	40.2	653.9	0.0
	Ignore CC/CC effects	153.9	93.0	672.5	12.7
80% CO_2 reduction	Ignore CC/no CC effects	252.9	40.9	653.9	0.0
	Plan for CC/CC effects	297.0	44.0	672.5	0.0
	Plan for CC/no CC effects	297.0	44.7	653.9	0.0
	Ignore CC/CC effects	252.9	44.9	672.5	1.0

Additionally, we found that fleets that achieve an 80% reduction in CO_2 emissions are less vulnerable to these estimated impacts of climate change. Because the capacity model needs to add more renewable capacity (wind and solar) to meet the stricter emission constraint, this results in excess generation capacity. This surplus capacity also helps to reduce climate-induced vulnerabilities even in the scenarios where the planning stage erroneously did not account for climate change impacts (*Ignore CC/CC occurs*).

There are some caveats in our analysis that should be taken into account when interpreting our results. First, while our expansion policies accounted for the uncertainty in climate projections, they were optimized assuming static scenarios. In these scenarios, 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 would adapt their decisions as they start to observe some of the 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. To represent a more realistic investment dynamics in the capacity expansion model, future extensions of this work could use a different approach that inherently included uncertainty and the acquisition of information during the planning stage (e.g., using a real options framework [26]).

Also, because our objective was 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 changes with climate-induced ones. For example, electrification of the transportation sector could increase total annual electricity consumption between 25% and 71% by 2050 [43]. Additionally, demand for ambient cooling – the main driver of the increase in lost load in our results – will also depend strongly on socio-economic factors such as its affordability [80]. Moreover, if population expands in our study region as expected [67], then we could expect climate change to cause a larger increase in demand, exacerbating planning and operational trade-offs found in our results.

We did not include transmission constraints, nor changes in solar and wind generation because of climate change. Transmission capacity is sensitive to ambient air temperature and climate change could result in additional transmission restrictions [58, 6]. Climate change could also affect solar and wind generation profiles [16, 17, 40], which could impact our results given the substantial participation of renewables in our future fleets. These climate impacts on renewable generation could be particularly important for scenarios with stringent carbon constraints. 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.

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. When we did not include climate-induced impacts in the operations stage (2050), the energy costs from the fleet planned including these impacts were 9% higher than the energy costs of the fleet planned ignoring these impacts. Conversely, when climate induced impacts were included, the energy costs from the fleet planned including these impacts were 60% lower than those of the fleet planned ignoring climate-induced impacts. 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 ambient cooling methods 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 80% CO_2 cap scenario. This dual benefit of these strategies (adaptation and mitigation) makes 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.

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