When Do Different Scenarios of Projected Electricity Demand Start to Meaningfully Diverge?

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Abstract
Resource adequacy studies look at balancing electricity supply and demand on 10- to 15-year time horizons while asset investment planning typically evaluates returns on 20- to 40-year time horizons. Projections of electricity demand are factored into the decision-making in both cases. Climate, energy policy, and socioeconomic changes are key uncertainties known to influence electricity demands, but their relative importance for demands over the next 10-40 years is unclear. The power sector would benefit from a better understanding of the need to characterize these uncertainties for resource adequacy and investment planning. In this study, we quantify when projected United States (U.S.) electricity demands start to meaningfully diverge in response to a range of climate, energy policy, and socioeconomic drivers. We use a wide yet plausible range of 21st century scenarios for the U.S. The projections span two population/economic growth scenarios (Shared Socioeconomic Pathways 3 and 5) and two climate/energy policy scenarios, one including climate mitigation policies and one without (Representative Concentration Pathways 4.5 and 8.5). Each climate/energy policy scenario has two warming levels to reflect a range of climate model uncertainty. We show that the socioeconomic scenario matters almost immediately – within the next 10 years, the climate/policy scenario matters within 25-30 years, and the climate model uncertainty matters only after 50+ years. This work can inform the power sector working to integrate climate change uncertainties into their decision-making.

Keywords
Electricity demand; load forecasting; emissions scenario; climate; socioeconomic scenario

1. Introduction

The first step in long-term energy system planning is often a scoping process that defines the system and clarifies the range of stressors to be accounted for including demand growth, technology innovation, market structure and regulation changes, policies, and climate. The next steps typically include developing infrastructure plans that provide the bulk power system with the desired ability to meet peak electricity demand for the least cost. Finally, the planning process stress tests the projected infrastructure to evaluate the economics of bulk system operations under extreme conditions and provide insights to justify future investments. Demand projections are a major driver across all steps of the integrated resources planning workflow. Note that we use the terms "demand" and "load" interchangeably throughout the paper. However, projecting electricity demand is a complex process because it depends on uncertain socioeconomic, policy, and climate changes (e.g., Zhang et al. 2022 and references therein). Retrospective analyses have shown that demand projections can be highly uncertain (e.g., Kaack et al. 2017 and Wachtmeister et al. 2018).

Climate change trends and interannual variability are increasingly being used as stressors in long-term planning exercises across the electricity sector (e.g., Cronin et al. 2018; Amorim et al. 2020; Harang et al. 2020; Khan et al. 2021; Plaga and Bertsch 2023). Climate change has been shown to impact both electricity supply and demand, requiring a shift in planning practices that have traditionally relied on historical weather patterns (e.g., Auffhammer et al. 2017; Steinber et al. 2020; Romitti and Sue Wing 2022). This need will amplify in the future due to the continued electrification of weather-sensitive energy services such as heating and cooling (Staffell and Pfenninger 2018) which will impact demand and the increasing penetration of weather-dependent renewable resources in the supply mix.

A major challenge for incorporating climate change into long-term energy planning is uncertainty over which climate models or climate scenarios to use. There is a vast universe of options. For example, over 50 research groups have submitted historical or future runs to Phase 6 of the Coupled Models Intercomparison Project (CMIP6; Ashfaq et al. 2022). Each group uses a particular General Circulation Model (GCM) to produce a range of simulations that span climate scenarios and physics configurations. At the time of writing there are over 450 unique climate simulations in the CMIP6 archive with more being added every day. To use even a single GCM run as a basis for exploring climate impacts on electricity supply and demand is a time consuming process. It involves, at a minimum, obtaining the raw output (often multiple terabytes), downscaling the model to the appropriate resolution, and post-processing it into the necessary format for detailed energy system modeling (e.g., wind, hydropower, load, and solar modeling). Given the time and labor involved, it is often impractical for any entity to use more than a small handful of climate projections as a basis for long-term planning. Additionally, different climate models can give drastically different projections of future conditions (e.g., Meehl et al. 2020). To make matters worse, even when using a single climate model, one can obtain a range of future conditions depending on the climate scenario or physics configuration that is chosen. For example, comparing low emissions with high emissions scenarios (e.g., Iyer et al. 2022; Nazarenko et al. 2022).

These challenges raise important questions for utilities and bulk power grid planning agencies: Which climate model(s) or scenario(s) should be used, if any, and what planning questions are they best suited to address? This study aims to provide some insights by focusing on how different climate projections affect electricity demand compared to the effects of alternative socioeconomic projections. While we present results out to the end of the century, much of the analysis is focused on the next 40 years given that integrated resource planning is typically performed with 10- to 20-year time horizons and technology-specific asset investment decisions are made with 20- to 40-year time horizons. If electricity demand projections using different climate models or climate scenarios do not diverge significantly in the typical planning periods, then it may not matter what climate data are used in the planning process.

We tackle this question by comparing load projections from a set of eight future scenarios that span a wide but plausible range of future climate, energy policy, and socioeconomic conditions. The scenarios were intentionally designed to reflect socioeconomic scenario uncertainty (i.e., low vs high population growth and labor productivity), climate policy and resulting future climate uncertainty (i.e., policies leading to moderate vs high greenhouse gas emissions and the associated decarbonization trends that accompany them), and climate model uncertainty (i.e., using models that are hotter or cooler than average). For each scenario we generated high-resolution climate and socioeconomic futures which were used in a multi-model framework to project annual and hourly electricity demands at multiple scales. We then did pairwise scenario comparisons to isolate the effects of socioeconomic scenario versus emissions scenario versus climate model choice on the evolution of load projections. By examining both the overall trends and changes in peak loads, we ensure that the projections are consistent and provide information that can be used across the spectrum of long-term planning exercises.

2. Methods

2.1 Climate and Socioeconomic Scenarios

The Integrated Multisector Multiscale Modeling (IM3; https://im3.pnnl.gov/) project has generated a set of eight scenarios for the conterminous United States (U.S.) that span a wide but plausible range of uncertainty in future climate and socioeconomic conditions (Fig. 1). We represent climate uncertainty with four high-resolution, dynamically downscaled climate simulations for the period 2020-2099 (Jones et al. 2023). These four simulations project future climate for two alternative greenhouse gas emissions trajectories, each with two sets of assumptions about the degree of future warming given a trajectory. The emissions scenarios are the Representative Concentration Pathways (RCPs) 4.5 and 8.5 (Moss et al. 2010). The RCP 8.5 scenario is a high emissions scenario while the RCP 4.5 scenario requires substantial emissions reductions in order to keep global radiative forcing less than 4.5 W m^{-2} before the year 2100. Achieving the RCP 4.5 scenario goal requires significant electrification of the buildings, transportation, and industrial sectors, which in turn results in higher overall electricity demand. While not explored in this study, the electrification rate in an RCP 2.6 scenario would need to be even higher than in the RCP 4.5 run (e.g., Clarke et al. 2022; Jay et al. 2023).

The two levels of future warming derive from uncertainties in the CMIP6 GCM model archive. We use the average warming values from groups of eight models that are either “cooler” or “hotter” than the multi-model mean. The climate simulations use an approach called Thermodynamic Global Warming (TGW) that “replays” 40 years of historical weather conditions (1980-2019) under future climate, using the RCP and hotter/cooler model combinations. The simulations repeat the historical period twice in sequence to produce future climate from 2020-2059 and from 2060-2099. Combining the emissions scenario uncertainty and climate model uncertainty yields four future 80-year hourly climate projections: *rcp45cooler*, *rcp45hotter*, *rcp85cooler*, and *rcp85hotter*. While these simulations do not directly address the potential increased frequency of extreme events, they do indicate how past events could increase in intensity, duration, and scope.

We create a total of eight future scenarios by combining each of the four climate futures with two socioeconomic scenarios (Fig. 1). The two socioeconomic scenarios, Shared Socioeconomic Pathways (SSPs) 3 and 5 (O'Neill et al. 2017), project future global populations and macroscale economic indicators (e.g., GDP). In the U.S., SSP3 reflects a low-growth population scenario while SSP5 is a high-growth population scenario. For example, total U.S. population in 2050 is 329 million for SSP3 and 430 million for SSP5 (Zoraghein and O'Neill 2020). The gridded and state-level population data we use for each SSP are documented in Jiang et al. (2020) and Zoraghein and O'Neill (2020). More information about how the SSPs were implemented within our multi-model workflow is provided in a companion paper (Zhao et al. 2024 – *In preparation*).

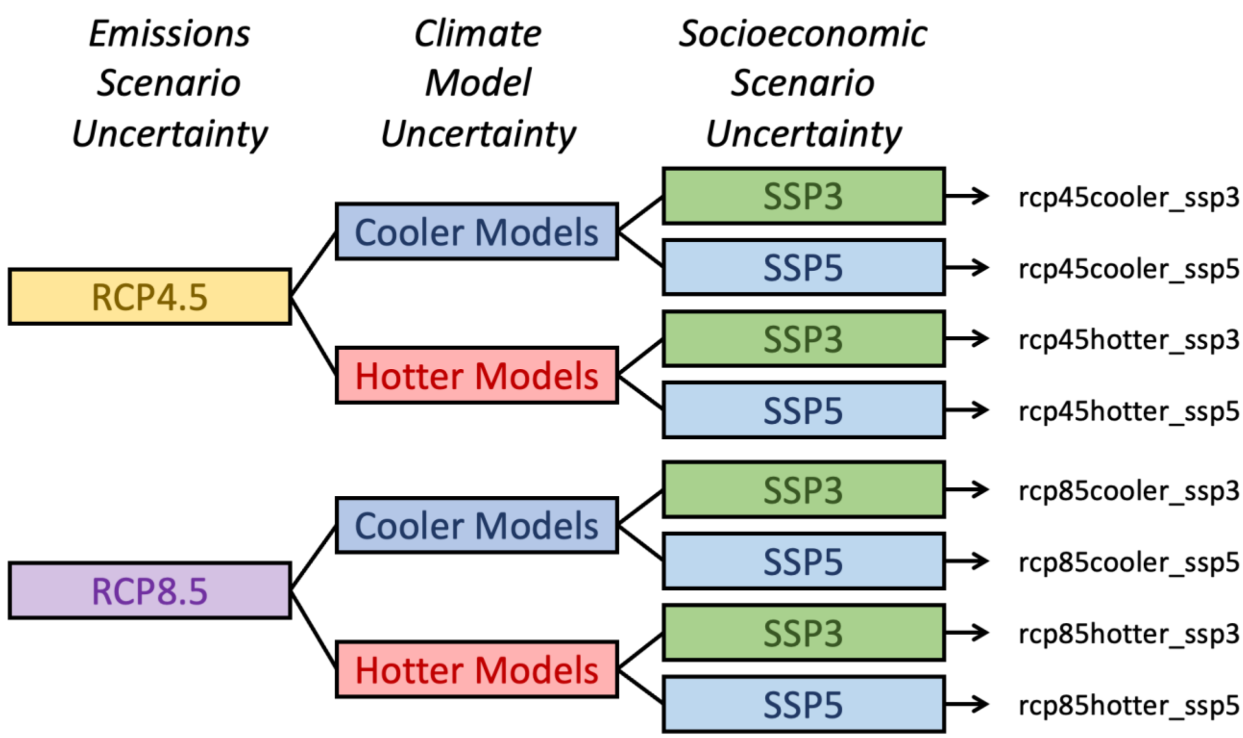

Fig. 1. The eight future scenarios reflect a range of socioeconomic scenario uncertainties, emissions scenario uncertainties, and climate model uncertainties.

The design of these scenarios allows us to isolate the impacts of our three main sources of uncertainty using pairwise comparisons where only one driver is different between the pair. For example, comparing electricity demand projections from the *rcp45cooler_ssp3* run with the *rcp45cooler_ssp5* run allows us to isolate the impact of socioeconomic uncertainty for the case of RCP 4.5 emissions and the cooler climate models. Completing the SSP comparison across the three other RCP/climate model pairs allows us to understand the overall importance of socioeconomic uncertainty for electricity demand and its interactions with emissions and climate model uncertainty. We perform these pairwise comparisons for each of the three sources of uncertainty (Table 1). The bulk of our analysis focuses on quantifying the year-by-year differences in mean and peak electricity demand across these pairs.

Socioeconomic Scenario Uncertainty [SSP3 vs SSP5]	Emissions Scenario Uncertainty [RCP 4.5 vs RCP 8.5]	Climate Model Uncertainty [Cooler vs Hotter Models]
rcp45cooler_ssp3 rcp45cooler_ssp5	rcp45cooler_ssp3 rcp85cooler_ssp3	rcp45cooler_ssp3 rcp45hotter_ssp3
rcp45hotter_ssp3 rcp45hotter_ssp5	rcp45hotter_ssp3 rcp85hotter_ssp3	rcp45cooler_ssp5 rcp45hotter_ssp5
rcp85cooler_ssp3 rcp85cooler_ssp5	rcp45cooler_ssp5 rcp85cooler_ssp5	rcp85cooler_ssp3 rcp85hotter_ssp3
rcp85hotter_ssp3 rcp85hotter_ssp5	rcp45hotter_ssp5 rcp85hotter_ssp5	rcp85cooler_ssp5 rcp85hotter_ssp5

Table 1. Groupings drawn from the eight IM3 scenarios in which there is only one variable different between the pair.

2.2 Load Models

We use a multi-model framework to generate hourly electricity demand projections for each the eight scenarios. The primary two models used in this experiment are a version of the Global Change Analysis Model with regional detail in the U.S. (GCAM-USA; Binsted et al. 2022 and Patel et al. 2024) and the Total ELectricity Loads (TELL; McGrath et al. 2022) model. An overview of the modeling chain and links to the source code for all models are provided at https://github.com/IMMM-SFA/exp_group_b. GCAM-USA simulates annual electricity demands (from buildings, transportation, and industry) at the state level and then TELL converts these to 8760-hr electricity demands based on hourly weather profiles from the TGW simulations.

GCAM-USA is a partial equilibrium model that simulates interacting markets for energy, water, and land over the 21st century within the U.S. and globally in response to specific RCP and SSP assumptions. GCAM-USA was recently used to support the U.S. long-term climate strategy (U.S. Department of State 2021). For our research, we utilized a GCAM-USA capability to incorporate scenario-based climate impacts on annual building energy demands (Zhao et al. 2024), agricultural yields (Ahsan et al. 2023), and water supply (Vernon et al. 2019).

The process for including climate impacts on building energy demands involves the upstream conversion of the TGW climate projections into annual population-weighted heating and cooling degree hours (HDHs/CDHs) for each U.S. state using the Helios model (Zhao et al. 2024). These HDH/CDHs are then used in GCAM-USA's building energy model to determine climate-sensitive electricity demands from residential and commercial buildings for each state and year of the simulation. More details about GCAM-USA's approach to projecting total electricity demand (i.e., from buildings, industry, and transport) are provided in Zhou et al. (2014), Clarke et al. (2018), and Binsted et al. (2022). In this experiment, GCAM-USA produced annual projections of state-level total electricity demand in 5-year increments from 2020-2095 for each of the eight scenarios. We also show annual historical electricity demands from 1980-

2019 to provide context for the future changes. Historical demands are from the U.S. Energy Information Administration's (EIA) State Energy Data System (SEDS).

Next, we passed the GCAM-USA annual electricity demand results to the TELL model. While GCAM-USA provides state-scale projections for total annual load, high spatial resolution hourly time series are needed to inform the integrated resources planning for its least cost operations and reliability performance metrics. TELL simulates hourly demands for electricity at the county, state, and Balancing Authority (BA) scale that are conceptually and quantitatively consistent with GCAM-USA's annual total demands (McGrath et al. 2022). TELL uses a machine learning approach to simulate hourly electricity demands that are responsive to variations in weather. The model then scales those results to match the annual state-level total loads from GCAM-USA. To force TELL, the raw TGW climate simulation data (Jones et al. 2022) were first spatially averaged by U.S. county (Burleyson et al. 2023a) and then population-weighted (based on the SSP populations) into 8760-hr meteorology time series for each BA (Burleyson et al. 2023b). GCAM-USA and TELL use the same climate and socioeconomic forcing and are therefore internally consistent. The benefit of including TELL in this experiment is that it allows us to simulate annual peak demands (derived from the 8760-hr profiles from each year) that complement the annual total load projections from GCAM-USA. This enables us to explore how changes in peak demands compare to changes in total demands over time and across scenarios.

2.3 Difference Calculations

To analyze the divergence in hourly loads between pairs of scenarios we computed the mean hourly absolute difference (in MWh) between a given pair of scenarios for each year in our model output (every 5 years). Relative differences were calculated by dividing the hourly absolute difference by the average hourly load between the pair. Relative differences are expressed as a percentage. To analyze changes in peak loads, we identified the single highest hourly load value from each 8760-hr time series in the pair and then computed the absolute difference between those peak values. Relative differences in peak loads were computed by dividing this absolute difference by the average of the pair. An example of these calculations for one pairwise comparison is shown in Fig. 2 for the year 2080 in the California Independent System Operator (CISO) BA.

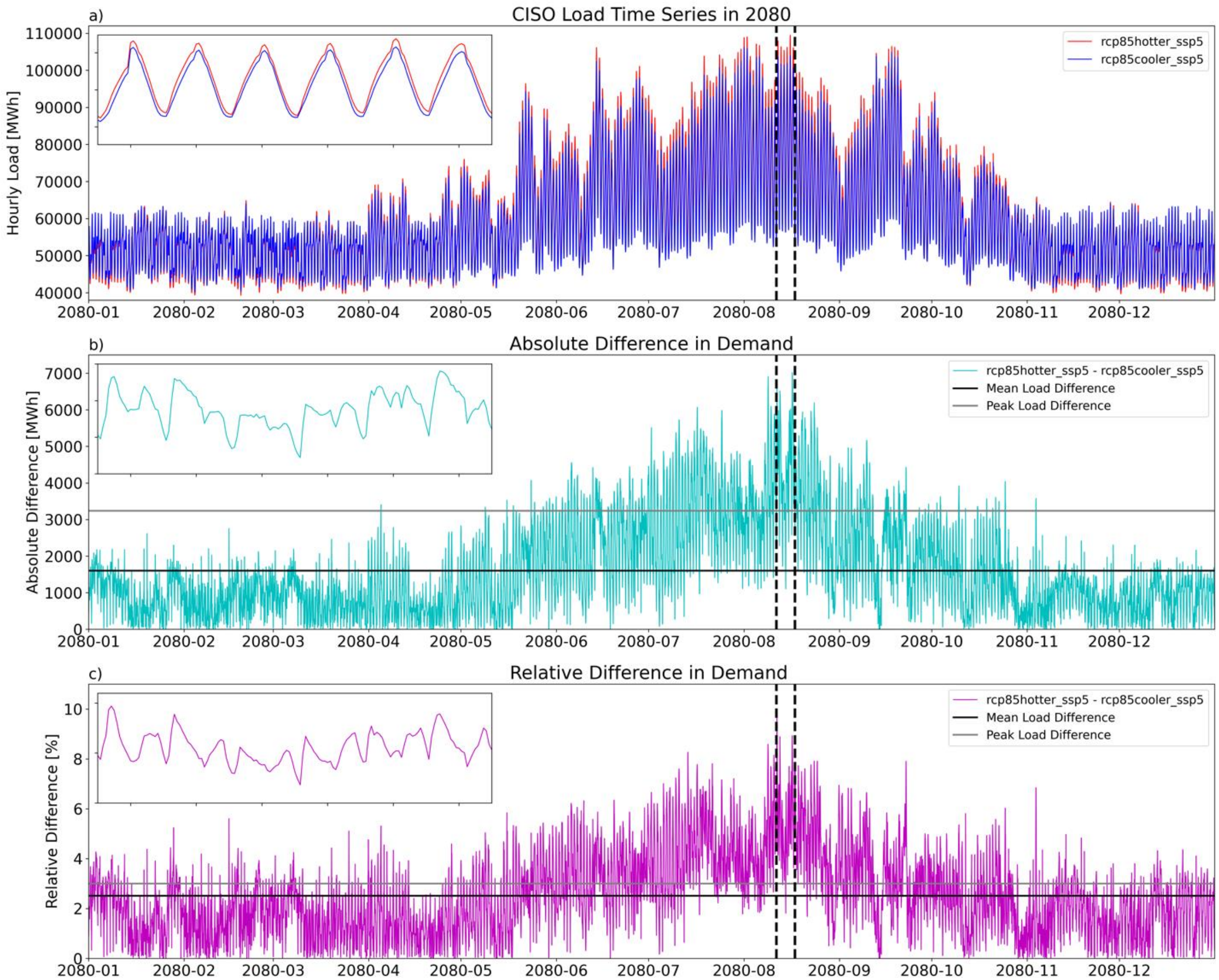

Fig. 2. Example of the calculation of mean and peak demand differences between the rcp85hotter_ssp5 and rcp85cooler_ssp5 scenarios for one year of TELL output in CISO: a) the 8760-hr time series from the pair of scenarios; b) the hourly absolute demand difference between the pair; and c) the hourly relative demand difference between the pair. The inset in each panel shows the values zoomed in for a one-week period (vertical dashed lines) during a heat wave. The y-axis limits on the insets are the same as the plot they are embedded in.

3. Results

We analyzed the TELL output at multiple scales including states, BAs, and across the three U.S. interconnections (eastern [EIC], western [WIC], and the Electric Reliability Council of Texas [ERCOT]). TELL produces load projections for 54 BAs in the conterminous U.S. A full list of the BAs, their names and acronyms, and their service territories are all available in the meta-repository that accompanies this paper (Burleyson et al. 2024): https://github.com/IMMM-SFA/burleyson-etal_2024_applied_energy/blob/main/Balancing_Authorities_Analysis.md. We start by looking at the raw time series of annual total and maximum load and then dig deeper by doing the pairwise scenario comparisons to quantify divergence. Finally, we analyze the spatial variability of the divergence signal and the divergence in the highest loads. While we show results out to 2100 for context, the first 20-to-40 future years are most insightful for informing long-term planning in the electric industry.

3.1 Electricity Demand Projections

Figure 3 shows the time series of projected annual total load and annual peak demand for each of the three electricity interconnections in the U.S. Demand was calculated by summing across the BAs in each interconnection. In this analysis peak demand is the single highest hourly load value each year. The interconnection time series are used as a canonical example – the patterns are similar across states and BAs. Because different stakeholders are interested in different scales, similar plots for each state and BA can be found in the meta-repository that accompanies this paper (https://github.com/IMMM-SFA/burleyson-etal_2024_applied_energy).

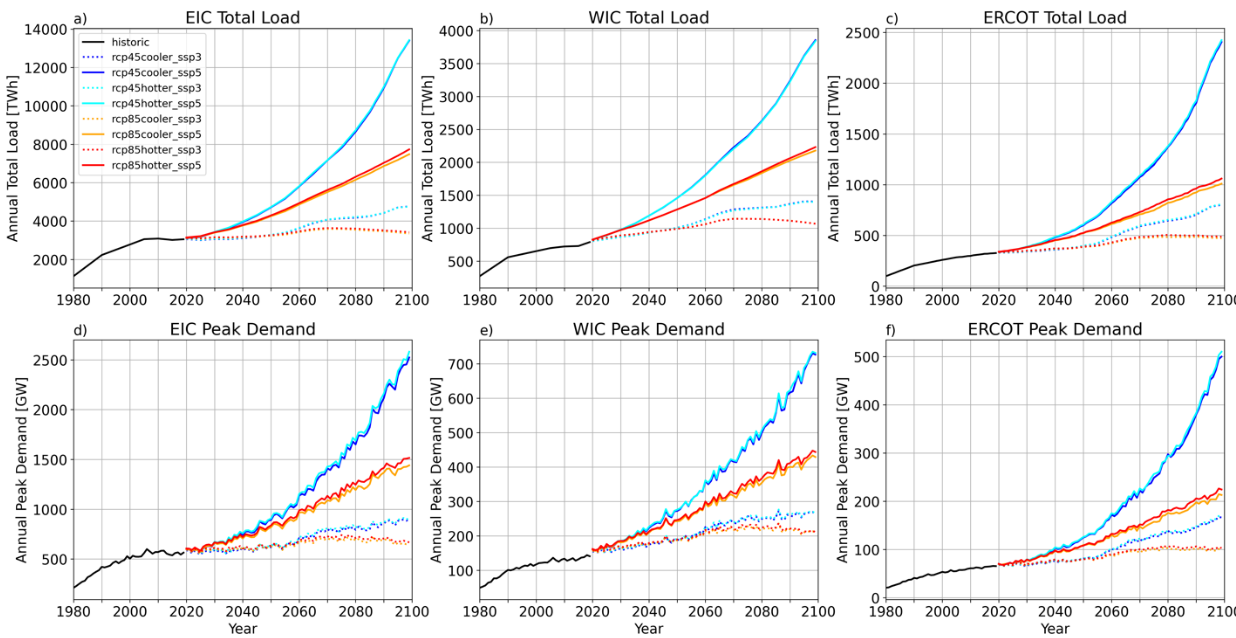

Fig. 3. Historical and projected annual total load (top row) and annual peak demand (bottom row) from 1980-2100. Projections using the SSP3 socioeconomic forcing are shown in the dashed lines while projections using the SSP5 forcing are solid lines. Climate scenarios are indicated by different color lines. The projections are shown for the three U.S. grid interconnections: the Eastern Interconnection (EIC; left column), Western Interconnection (WIC; center column), and Electricity Reliability Council of Texas (ERCOT; right column).

Two dominant patterns appear in all three interconnections. First is the split between the projections based on the SSP5 scenario (solid lines) and those based on the SSP3 scenario (dashed lines). Because of the substantially larger population changes in SSP5 (31% more people by 2050 compared to SSP3; Zoraghein and O'Neill 2020), loads naturally grow at a faster rate for those projections. Loads in the SSP3 runs are flat or minimally increasing between 2020 and 2050 – consistent with the trend over the last 10 years of the historical period.

The second clear signal is the split between the RCP 4.5 (lines in shades of blue) and RCP 8.5 scenarios (lines in shades of red). This divergence appears later in all three interconnections compared to the SSP3-SSP5 split. All else being equal, one might expect the warmer climate in the RCP 8.5 scenarios to result in higher electricity demands than in the cooler climate of RCP 4.5. However, the GCAM-USA modeling imposes emissions constraints to achieve the RCP 4.5 scenario and this results in widespread electrification in the building, transportation, and industrial sectors. All three interconnections show an earlier and larger divergence between the RCP 4.5 and 8.5 projections for the SSP5 runs compared to the SSP3 runs. This is because the higher populations in SSP5 require earlier and more rapid decarbonization to keep on track with the RCP 4.5 emissions constraints.

In contrast to the SSP and RCP uncertainty results, for the climate model uncertainty pairs (e.g., *rcp85hotter_ssp3* vs *rcp85cooler_ssp3*) we see no discernable differences between the cooler and hotter model pairs for the first 40 years. However, after ~2060 the differences gradually become more apparent. By the end of the century, runs based on the hotter models have higher total and peak loads compared to the cooler models. The divergence between climate model pairs is most clear for the RCP 8.5 scenario projections.

Figure 4 shows the distribution of future load changes across BAs. In this and other boxplots in the paper the whiskers extend to the first and fourth quartiles and the dots indicate values more than 1.5x the interquartile range beyond the upper and lower quartiles. All future load values are normalized to 2019 (the last historical year) to facilitate comparison across BAs with drastically different absolute loads. The split between SSP3 and SSP5 projections is readily apparent as is the electrification enhancement in total and peak loads in the RCP 4.5 emissions scenario compared to the RCP 8.5 runs. This plot also clearly demonstrates that peak loads change at a slightly faster rate compared to total loads. For example, by 2060 the median peak demand change for the *rcp45cooler_ssp5* scenario exceeds ~2.3x the 2019 values whereas the median total load change is ~2.1x the 2019 value. These boxplots also allow us to study the distribution across BAs. Across all years and scenarios, the distributions are largely Gaussian with a slight skewness towards higher values that becomes more apparent in the later decades. Results for the distribution of changes across states are similar (not shown). The distribution across BAs and states suggests that while load in some areas changes faster or slower than others there are no major persistent outliers that would lead to drastically skewed distributions.

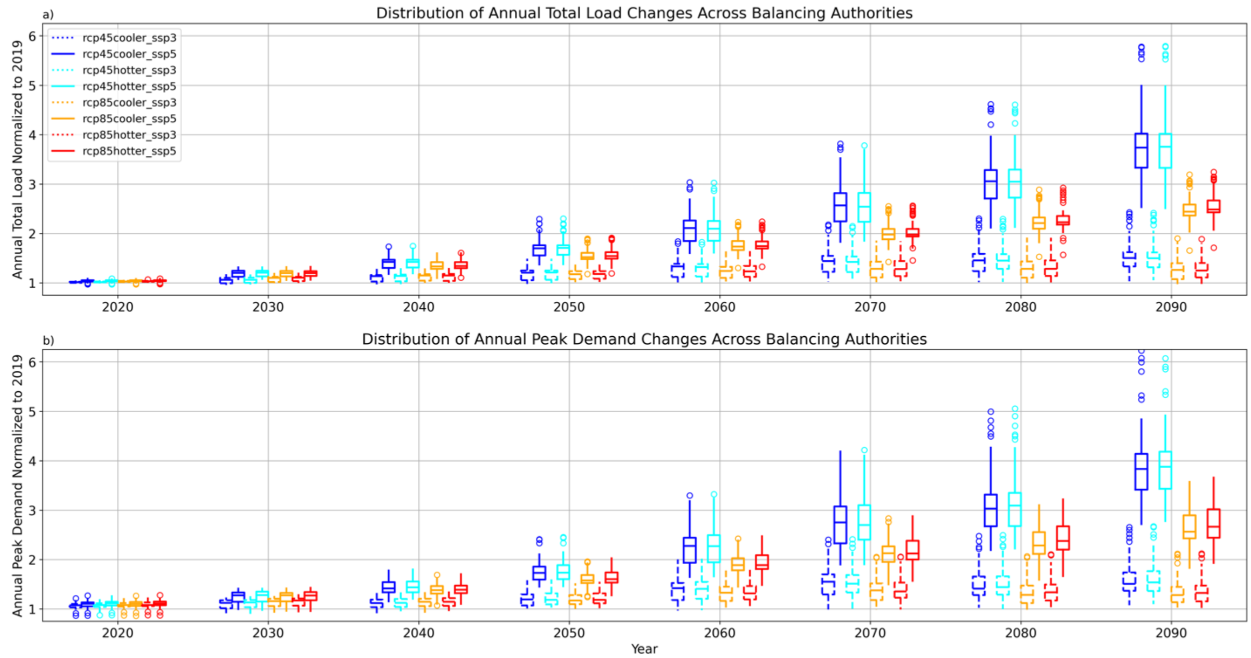

Fig. 4. Distribution across BAs of the change in annual total load (top row) and annual peak demand (bottom row) from 2020-2090 for each of the eight scenarios. Data is shown in 10-year increments to reduce clutter. Values are normalized to the 2019 historical loads to facilitate comparison across BAs and over time.

3.2 Load Divergence

We will start the divergence analysis by focusing on a single entity, in this case the Arizona Public Service (AZPS) BA, to understand the dominant patterns and then zooming out to look at the distribution of divergence across the full range of BAs simulated by TELL. The BA scale is used in this analysis because it is the most common framing for long-term planning. Figure 5 shows the evolution of the average relative difference between pairs of simulations in which only one variable differs. See Fig. 2 for an example of how the relative differences were computed and Table 1 for a list of all 12 pairs of scenarios.

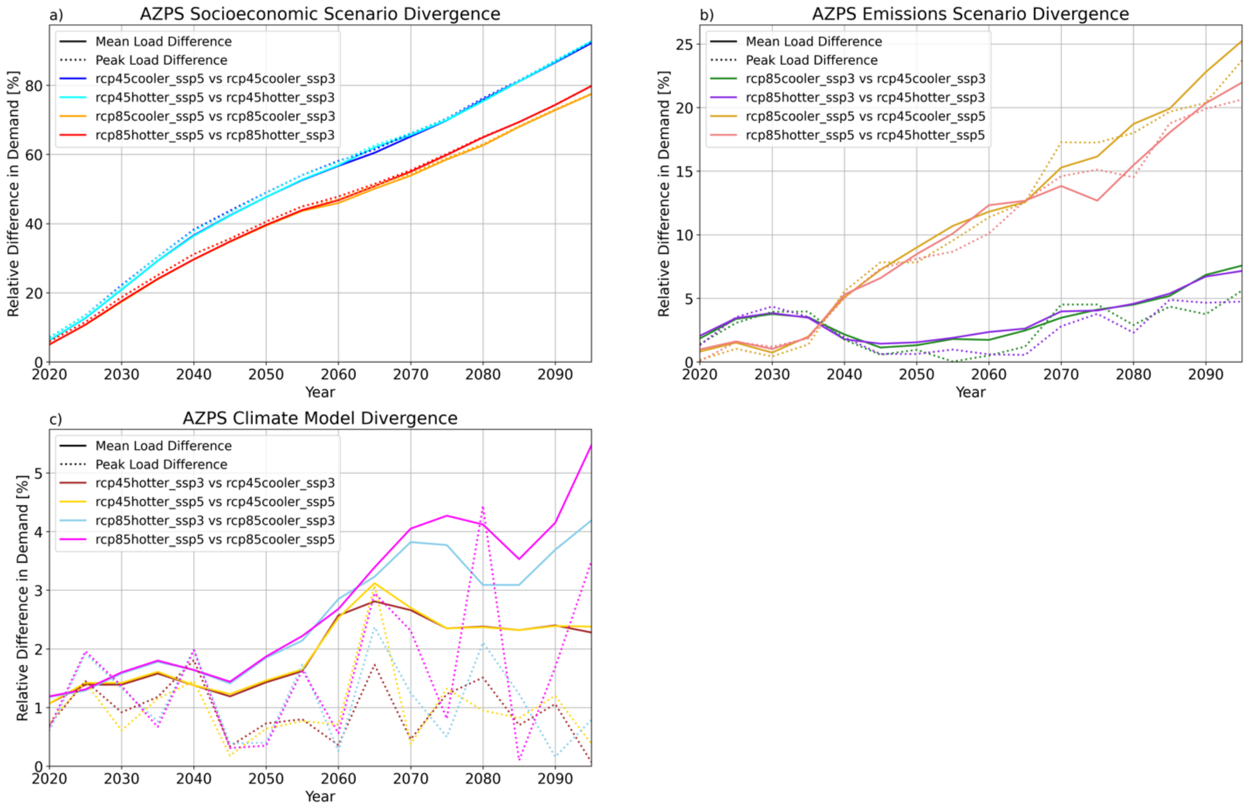

Fig. 5. Annual mean relative difference in demand between pairs of load projections for AZPS. The pairs are designed to span a range of a) socioeconomic scenario uncertainty (i.e., SSP3 vs SSP5), b) emissions scenario uncertainty (i.e., RCP 4.5 vs RCP 8.5), and c) climate model uncertainty (i.e., using warming derived from cooler vs hotter models). Mean differences across all 8760 hours are shown in the solid lines and mean differences for the peak load hours are shown in the dashed lines.

Starting with the socioeconomic scenario uncertainty, the strong and early divergence between pairs of simulations that use the SSP3 socioeconomic forcing compared to those using the SSP5 forcing is clear (Fig. 5a). Differences in 2030 are on average 16-22% and by 2050 they exceed 40% across all four pairs of scenarios. End-of-century differences between SSP3 and SSP5 runs are greater than 75%. Socioeconomic scenario differences are slightly higher in the pairs of simulations that use the RCP 4.5 emissions scenarios compared to those that use RCP 8.5 forcing. This is due to the electrification in the RCP 4.5 runs which is accelerated in the higher U.S. population in SSP5 compared to SSP3.

Moving to the emissions scenario divergence results (Fig. 5b), the first thing to point out is the difference in y-axis range compared to the SSP divergence plot. By 2050 the maximum difference between pairs is approximately 8%. This is in stark contrast to the SSP differences which all exceed 40% by 2050. Average differences between the RCP 4.5 and RCP 8.5 emission scenario pairs in AZPS do not exceed 5% until 2040 for the SSP5 pairs and until 2085 for the SSP3 pairs. End-of-century differences across emissions scenario pairs are less than 25%. Note that the initially higher difference values for the SSP3 runs may be an artifact of how we do the relative difference calculation. Because we normalize by average loads, the SSP5 runs will have a slightly smaller relative difference for a given absolute difference (because loads are higher in the SSP5 runs). This artifact does not impact the interpretation of our results.

Differences are even smaller when comparing pairs of scenarios that span a range of climate model uncertainties (Fig. 5c). Here the largest differences in the AZPS BA are less than 5.5% even at the end of the runs in 2095. They do not even exceed 3% difference until mid-century. This is clear evidence that the sensitivity of load projections to the choice of climate model (e.g., using cooler vs hotter models) may be minimal even on very long time horizons. The apparent increased noisiness in Fig. 5c is likely a plotting artifact stemming from the smaller y-axis range that allows year-to-year variability to become more apparent than the other scenario comparison plots.

The results for AZPS are broadly representative of the distribution of relative changes across BAs (Fig. 6). The distribution of changes between the socioeconomic scenario pairs are largely Gaussian (Fig. 6a). As with the results from AZPS, there is no clear distinction between the mean and peak load changes in Fig. 6a. The emissions scenario and climate model divergence plots (Fig. 6b,c) have significantly more spread. This indicates that climate/emissions sensitivity has more BA-by-BA variability compared to socioeconomic scenario sensitivity. Additionally, both the emissions scenario and climate model divergence plots also indicate a higher relative difference in mean loads compared to peak loads. This is particularly evident later in the century in the emissions scenario divergence plots (Fig. 6b) where the median mean load differences are 2-3% larger than the peak load differences. Similar patterns are found when analyzing the distribution of changes across states (not shown).

Fig. 6. Distribution across BAs of the relative difference between pairs of load projections from 2020-2090 spanning a) socioeconomic scenario uncertainty (i.e., SSP3 vs SSP5), b) emissions scenario uncertainty (i.e., RCP 4.5 vs RCP 8.5), and c) climate model uncertainty (i.e., using warming derived from cooler vs hotter models). Data is shown in 10-year increments to reduce clutter. Mean differences across all 8760 hours are shown in the solid lines and mean differences for peak load hours are shown in the dashed lines.

3.3 Classification of BAs According to Degree of Scenario Impacts on Demand

The goal of the next analysis is to explore if there are particular BAs, or groups of BAs, that are more or less sensitive to socioeconomic scenario, emissions scenario, or climate model uncertainty. Table 2 lists the BAs with the smallest and largest mean relative differences in the year 2050 across all 12 pairs of scenarios. While the results for emissions scenario sensitivity are a bit mixed, there were clear patterns for the pairs of scenarios spanning socioeconomic and climate model uncertainties. For socioeconomic scenario uncertainty, three BAs in different regions of the country (NYIS, WAUW, and LDWP) had consistently smaller differences whereas three BAs in the southwest (SRP, TEPC, and AZPS) demonstrated consistently higher sensitivities to socioeconomic scenario. A similar dipole exists for climate model sensitivity with the smallest sensitivities in the northwest (PSEI, SCL, TPWR, and GCPD) and the largest sensitivity to climate model in the southeast (GVL, NSB, and AECI). It is important to keep the overall magnitude of changes in mind for the climate model sensitivity analysis. Despite the consistently larger sensitivities in the southeast (Table 2) the largest differences are still only ~8% by the end of the century (Fig. 6c).

	Scenario Pair	Five Smallest Mean Differences in 2050	Five Largest Mean Differences in 2050
Socioeconomic Scenario Uncertainty	rcp45cooler_ssp3 rcp45cooler_ssp5	**NYIS**, **WAUW**, ISNE, IID, **LDWP**	SC, PNM, **SRP**, **TEPC**, **AZPS**
	rcp45hotter_ssp3 rcp45hotter_ssp5	**NYIS**, **WAUW**, ISNE, IID, **LDWP**	PSCO, PNM **SRP**, **TEPC**, **AZPS**
	rcp85cooler_ssp3 rcp85cooler_ssp5	**NYIS**, **WAUW**, NWMT, IID, **LDWP**	SCEG, SC, **SRP**, **TEPC**, **AZPS**
	rcp85hotter_ssp3 rcp85hotter_ssp5	**NYIS**, **WAUW**, NWMT, IID, **LDWP**	SCEG, SC, **SRP**, **TEPC**, **AZPS**
Emissions Scenario Uncertainty	rcp45cooler_ssp3 rcp85cooler_ssp3	NWMT, PGE, IPCO, NEVP, PJM	SWPP, **WACM**, **PSCO**, NYIS, ISNE
	rcp45hotter_ssp3 rcp85hotter_ssp3	NWMT, NEVP, IPCO, PGE, SRP	**WACM**, **PSCO**, NYIS, AECI, ISNE
	rcp45cooler_ssp5 rcp85cooler_ssp5	HST, FPL, SCEG, SC, FMPP	AECI, SWPP, PNM, **PSCO**, **WACM**
	rcp45hotter_ssp5 rcp85hotter_ssp5	FPL, HST, SCEG, FMPP, SC	SWPP, AECI, PNM, **PSCO**, **WACM**
Climate Model Uncertainty	rcp45cooler_ssp3 rcp45hotter_ssp3	**PSEI**, **SCL**, **TPWR**, BPAT, **GCPD**	ISNE, TAL, **GVL**, **NSB**, **AECI**
	rcp45cooler_ssp5 rcp45hotter_ssp5	**PSEI**, **SCL**, **TPWR**, BPAT, **GCPD**	HST, TAL, **GVL**, **NSB**, **AECI**
	rcp85cooler_ssp3 rcp85hotter_ssp3	**SCL**, **GCPD**, **PSEI**, **TPWR**, NWMT	ISNE, **GVL**, AEC, **NSB**, **AECI**
	rcp85cooler_ssp5 rcp85hotter_ssp5	**SCL**, **GCPD**, **PSEI**, **TPWR**, NWMT	ISNE, **GVL**, AEC, **NSB**, **AECI**

Table 2. List of the five BAs with the smallest and largest mean relative load differences in the year 2050 for each of the twelve pairs of scenarios. BAs that appear on the list for all four pairs of scenarios for a given source of uncertainty are shown in bold.

3.4 Spatial Patterns

Next we analyze the spatial characteristics of the load divergence. For this we focus on a subset of the pairs of scenarios to reduce the number of required plots and use state-level instead of BA-level data to facilitate easy plotting. Similar maps for each of the 12 pairs of scenarios can be found in the meta-repository that accompanies this paper (https://github.com/IMMM-SFA/burleyson-etal_2024_applied_energy). Figure 7 shows the spatial distribution of the first year in which the peak load difference exceeds 5% for the three sources of uncertainty. The threshold of 5%, although arbitrary, represents a finite difference beyond which you might reasonably be expected to be concerned about getting drastically different outcomes when using the scenarios for long-term planning. Similar results are found if you use a 10% or higher threshold (not shown). Looking at this data in a map format helps to understand some of the differences in the sensitivity to climate scenario and climate models (Fig. 6b,c and Table 2).

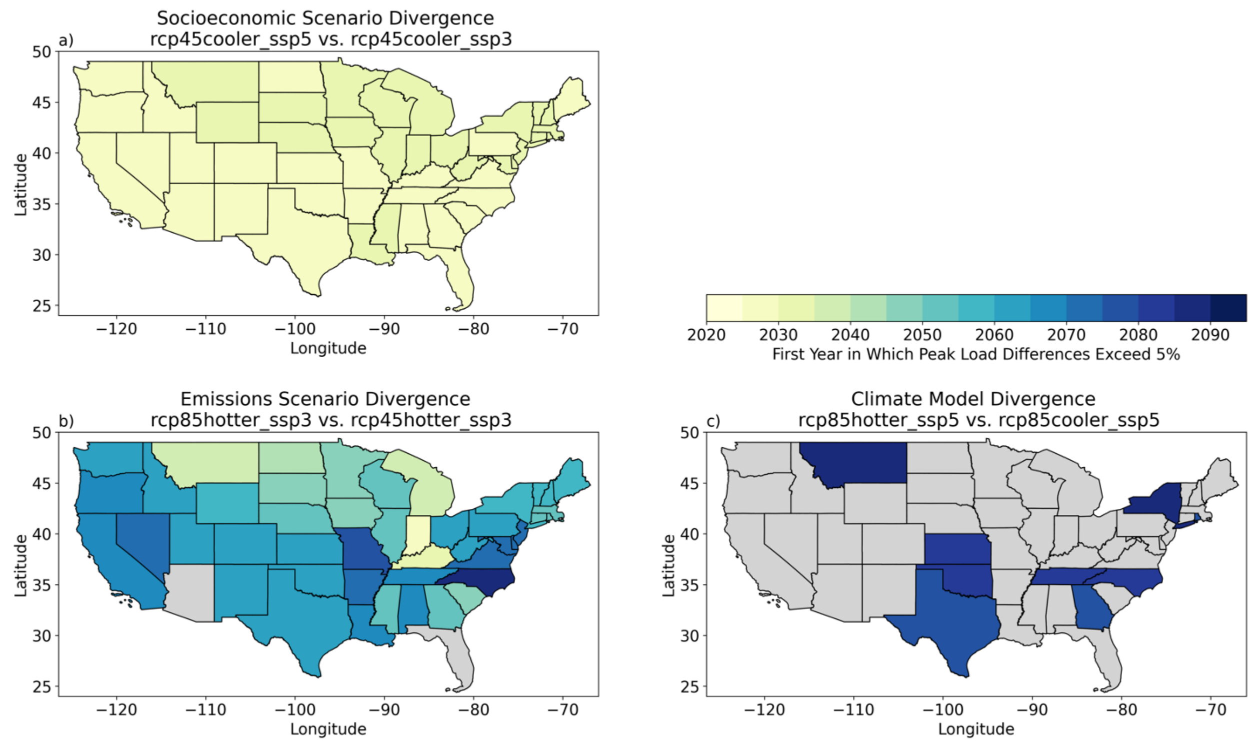

Fig. 7. Maps showing the first year in which the peak load difference between three pairs of scenarios (shown in the title of each subplot) exceeds 5%. Grey shading indicates states that never experience differences larger than 5%.

Consistent with the results shown in Fig. 6, all states experience socioeconomic scenario divergence at roughly the same pace (Fig. 7a). While there are minor variations from state-to-state, all 48 states shown have a difference greater than 5% by 2040 at the latest. Some of the larger population states (i.e., Florida and California) experience slightly later divergence – a finding that could be due to the normalization artifact discussed previously. If the states have a naturally larger electricity demand, then they would experience smaller relative changes for a given absolute change.

As with the earlier analyses, the more interesting results come from exploring the emissions scenario and climate model divergence (Fig. 7b,c). In both plots there is significantly more state-to-state variability. In the case of emissions scenario divergence, the maps show a slight north-to-south gradient with earlier climate scenario impacts occurring in northern states compared to southern states (Fig. 7b). This effect appears marginal and may be due to the impact of electrified heating in the RCP 4.5 scenarios having an outsized impact on northern states with high heating demands. Two hot southern states, Florida and New Mexico, never experience emissions scenario divergence in peak loads that exceeds 5%. This is likely due to their already high cooling demand and year-round lack of heating demand that might increase due to electrification of heating in the RCP 4.5 climate scenario. For climate model divergence, there are no obvious spatial patterns for the pair of scenarios shown (Fig. 7c). Notably, the majority of states never actually experience peak load differences that exceed 5%.

3.5 Impacts on "Peakiness" of Load Duration Curves

Our final analysis looks at the change in peak loads across scenarios. Figure 4 showed that peak loads are increasing faster than mean loads and that the increase is scenario dependent. We dive into this further by examining changes in the extreme values of the Load Duration Curves (LDCs) for each BA. Figure 8 shows an example of the method for the PJM BA in the eastern U.S. The inset of Fig. 8 shows that the loads in PJM are becoming "peakier" over time. That is, the frequency of loads that are close to (defined here as >90%) the annual maximum load increases over time and that the amount of increase is scenario dependent. For this analysis we calculated the annual mean change in the number of hours with loads that exceed 90% of the annual maximum value. This normalization allows us to compare LDC shapes across scenarios with drastically different absolute loads. For this weather year in PJM, that increase is roughly +125 hours for the *rcp85hotter_ssp5* scenario compared to the historical value (~130 hours). Because the shape of the LDCs is only dependent on the climate forcing we leave comparisons across the two socioeconomic scenarios out of this analysis and focus only on the SSP5 set of runs.

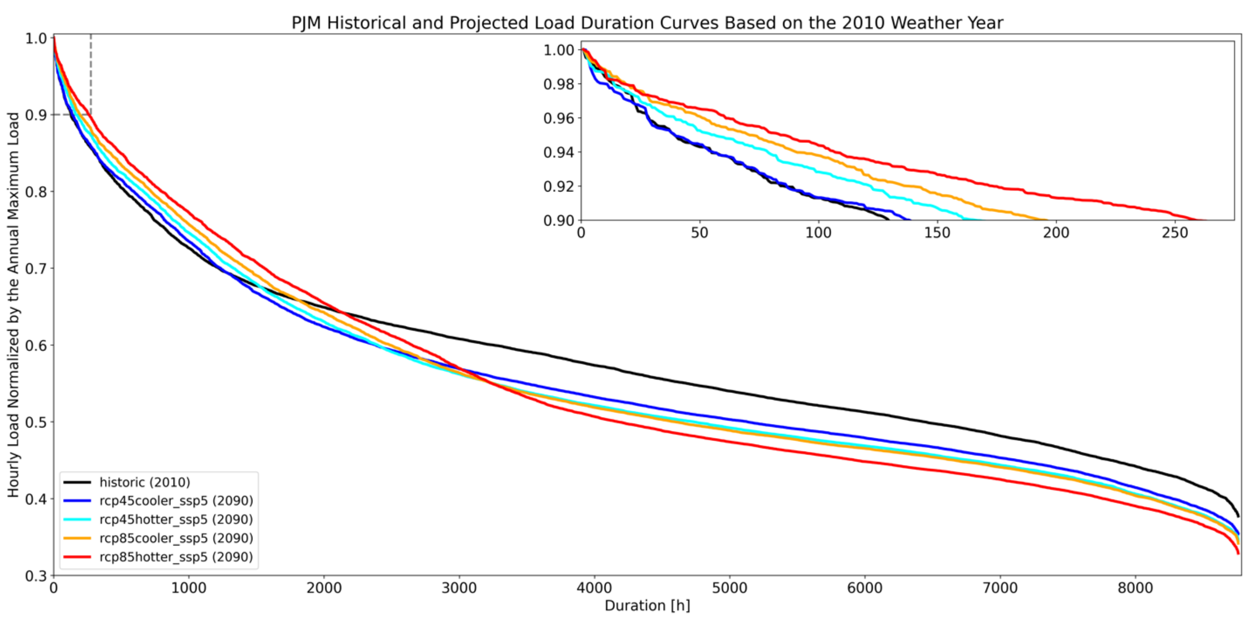

Fig. 8. Annual LDCs for the PJM BA for a single historical year (black line) and across the four future climate scenarios (colored lines). For this example, we used the 2010 weather year which is then repeated twice in the future projections (2050 and 2090). All hourly load values in each year and scenario are normalized by the annual maximum hourly load to compare LDCs across years and scenarios. The inset highlights changes in the peak loads.

Over the first forty future years in our analysis (2020-2059) there is evidence that the loads in most BAs become slightly peakier (Fig. 9a). For all but a small handful of BAs and scenarios this change is, on average, less than an additional 50 hours per year in which loads exceed 90% of the annual maximum load. Notable exceptions to this pattern include AECI, JEA, and SPA which have anomalously high changes in peak loads and HST and NWMT where the loads become less peaky over time. Importantly for this analysis, there is little scenario divergence within the first forty years (i.e., the different colored dots for a given BA largely overlap). This is in stark contrast to the signal in the second half of the century where the trend towards peakier loads accelerates and there is a noticeable difference across the four climate scenarios (Fig. 9b). For some BAs and scenarios, the change exceeds 100 hours per year compared to the historical frequency. In almost every BA the loads driven by the RCP 8.5 climate forcing are peakier compared to those from the RCP 4.5 forcing. The same is true for the hotter versus cooler climate forcing.

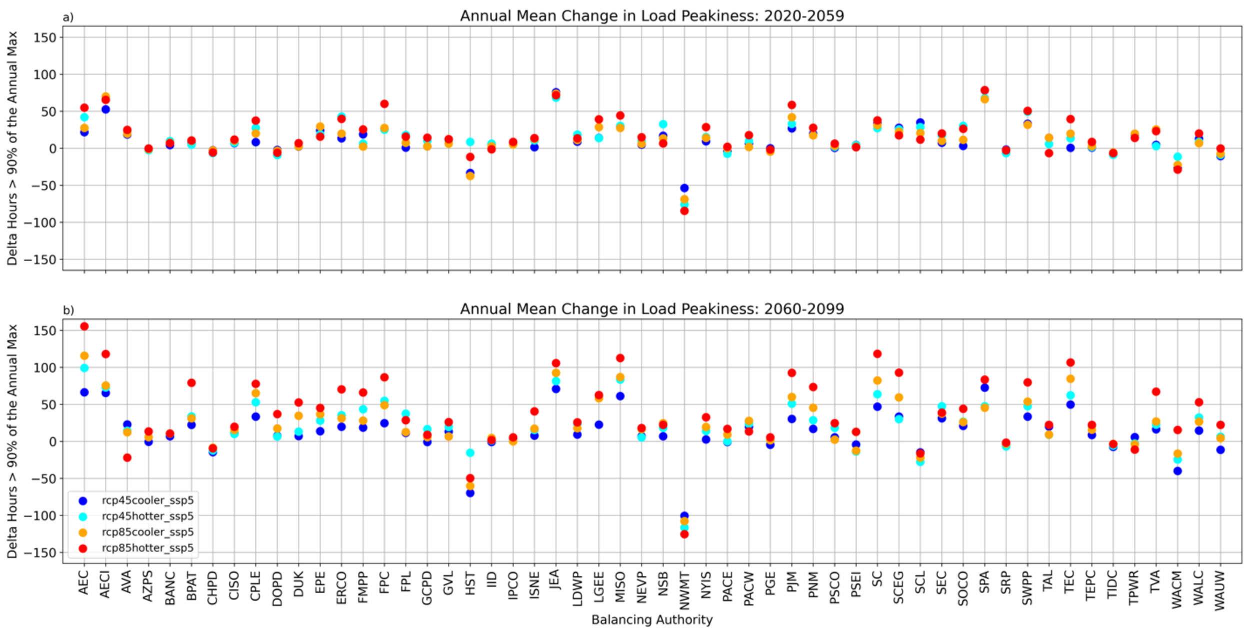

Fig. 9. Changes in the number of hours with loads that exceed 90% of the annual maximum load (y-axes) by BA (x-axes). The top row shows the mean change by BA from 2020-2059 (i.e., the first repeat of the 40-year historical variability) and the bottom row shows the mean change from 2060-2099 (i.e., the second repeat). The different colors represent the four climate scenarios used in this analysis.

4. Conclusions and Discussion

This work explored the divergence of electricity demand projections across eight combined climate and socioeconomic scenarios. The scenarios were intentionally designed to span a wide but plausible range of socioeconomic scenarios, emissions scenarios, and climate model uncertainties. We ran the scenarios through the GCAM-USA and TELL models to produce 80 years of projected hourly total electricity demand at the state- and BA-scale. By comparing pairs of projections where only one variable differs between the pair we can understand when the uncertainty captured by different facets of the scenarios becomes relevant. For example, when does it matter if you use the RCP 4.5 or RCP 8.5 emissions scenario as a basis for your long-term load projections?

The primary results are as follows:

1) Socioeconomic scenario uncertainty (i.e., SSP3 vs SSP5) matters almost immediately - within the first 10 years. Because of the significantly higher populations in the SSP5 scenario compared to SSP3, annual loads from the SSP5 group are 5-15% higher by 2030 and more than 25% higher by 2050 (Fig. 6a). By 2090, mean differences between the SSP3 and SSP5 projections exceed 60%. These clear and definitive divergence patterns demonstrate the critical importance of including socioeconomic scenario uncertainty in projections of electricity demand for long-term planning.

2) The annual load difference between emissions scenarios (i.e., RCP 4.5 vs RCP 8.5) are smaller and appear later than the socioeconomic scenario differences (Fig. 6b). The primary driver of the difference between the two climate scenarios is the higher degree of decarbonization and electrification needed to achieve the RCP 4.5 emissions pathway compared to RCP 8.5. Average differences between the RCP 4.5 and RCP 8.5 scenario pairs do not exceed 5% until mid-century (Fig. 6b). Average differences in 2090 due to climate scenario uncertainty are less than 45%. While not negligible, this result suggests that choosing the correct emissions scenario may not matter within the 10-20-year decision horizon typically used in long-term planning. There is a marginal north-south gradient in the impact of climate scenario with northern states experiencing slightly earlier climate scenario divergence compared to southern states (Fig. 7b and Table 2).

3) The divergence between pairs of projections that reflect climate model uncertainty (i.e., whether you use hotter or colder climate models to derive future climate forcing) are even smaller than the climate scenario uncertainty (Fig. 6c). Even by 2090 the mean differences barely exceed 4%. This is 10x smaller than the end-of-century differences due to emissions scenario and 15x smaller than the differences due to socioeconomic scenario selection. There was a regional dipole in the climate model sensitivity. In 2050 the smallest sensitivities were for BAs in the northwest (PSEI, SCL, TPWR, and GCPD) while the largest sensitivity to climate model uncertainties were in the southeast (GVL, NSB, and AECI). This suggests that utilities and planning agencies focused on the southeastern region of the U.S. should be more cautious when selecting which scenarios and models to use as a basis for long-term planning.

4) Our analysis showed that loads in almost every BA become peakier over time in all scenarios. This was measured by quantifying the change in the number of hours that exceed 90% of the annual maximum load by BA. However, within the first forty years of our analysis (2020-2059) the increase in peakiness was relatively small (<50 hours) and uniform across emissions scenario and climate model runs. Divergence in the peakiness analysis appears after 2060 with the largest increases in peak loads coming from the RCP 8.5 climate scenario and the hotter climate models. This analysis demonstrates that long-term planning

exercises focused on peak loads should be cautious about their choice of scenario and model in the latter half of the century but less concerned before 2060.

There are several limitations to this study. As with most research they can easily be reframed as opportunities for extension of this work. First, the results were obtained using a specific set of scenarios and load models (GCAM-USA and TELL) and thus have some natural degree of tool-dependence. For example, due to structural differences, other GCAM-class models may produce different load projections given a common set of forcings (not shown). Our results may also be specific to the unique characteristics of the U.S. energy system. While it is beyond the scope of this study to explore the questions posed using a wider range of scenarios and tools, doing so would obviously add confidence to the results. The socioeconomic scenarios we chose to explore were intentionally very different from one another. This allows us to cover a wide range of uncertainty in this space. However, repeating this study with, for example, the SSP2 population and socioeconomic scenario would almost certainly result in a smaller and later divergence point for the socioeconomic scenario divergence analyses. Likewise, using an RCP 2.6 scenario (for example) would likely lead to much more rapid electrification than even the RCP 4.5 run and thus earlier divergence across RCP scenarios. However, it seems unlikely that these choices would change the main result that socioeconomic scenarios diverge earlier than climate scenarios or climate models – a finding that is consistent with prior results showing the importance of socioeconomics over climate on future loads (e.g., Zhou et al. 2014; Huang and Gurney 2016; and Burillo et al. 2019). Finally, we note that detailed end-use impacts on hourly demand profiles such as from the electrification of heating are not directly captured by the TELL model. Exploring the impacts of heating electrification on hourly demand under climate and socioeconomic change would make for an interesting follow-on analysis.

Collectively, our findings suggest that in order of relative importance for understanding load projections for long-term planning, the planner's choice of socioeconomic scenario (SSP3 vs SSP5) matters almost immediately, their choice of climate/emissions scenario (RCP 4.5 vs RCP 8.5) and the associated decarbonization implications that come with it matters within 25-30 years, and their choice of whether to use hotter or cooler climate models matters only after 50+ years.

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