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ENERGY RESEARCH AND DEVELOPMENT DIVISION

Appendix B: Climate-Informed Load Forecasting for California Interim Report

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Climate-Informed Load Forecasting for California

Interim Report

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Energy+Environmental Economics

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Contribution to California's Fifth Climate Change Assessment

This Interim Report describes original, energy-related research that contributes to California's Fifth Climate Change Assessment (Fifth Assessment). The Fifth Assessment comprises a broad portfolio of research and synthesis reports that address California-specific research needs and knowledge gaps related to climate change. To ensure scientific rigor, Fifth Assessment research was peer reviewed. This research effort was peer reviewed through an editorial board established for the Fifth Assessment, which also served (where applicable) to support appropriate representation of the practitioners and stakeholders to whom each report applies.

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CALIFORNIA'S FIFTH
CLIMATE CHANGE
ASSESSMENT

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Acronym Definitions

Acronym	Definition
AC	Air Conditioning
AUC	Area Under the Curve
BAAQMD	Bay Area Air Quality Management District
BAU	Business-as-usual
CAISO	California Independent System Operator
CAVA	Climate Adaptation Vulnerability Assessment
CEC	California Energy Commission
CFL	Compact fluorescent lamp
CCS	Carbon Capture and Storage
CDD	Cooling Degree Day
CMIP6	Coupled Model Intercomparison Project, Phase 6
COP	Coefficient of Performance
CPUC	California Public Utilities Commission
EIA	U.S. Energy Information Administration
ERA5	European Centre for Medium-Range Weather Forecasts Reanalysis v5
GCM	Global Climate Model
GHG	Greenhouse Gas
GWL	Global Warming Level
HDD	Heating Degree Day
IEPR	Integrated Energy Policy Report
IPCC	Intergovernmental Panel on Climate Change
IRP	Integrated Resource Plan
LBNL	Lawrence Berkeley National Laboratory
LDV	Light-duty Vehicle
LOCA2	Localized Constructed Analogs version 2
LSE	Load Serving Entity
MHDVs	Medium- and Heavy-Duty Vehicles
OGV	Ocean-going vessel
RAMP	Risk Assessment Mitigation Phase
RASS	Residential Appliance Saturation Study
SCAQMD	South Coast Air Quality Management District
SSP	Shared Socioeconomic Pathway
WECC	Western Electricity Coordinating Council
WRF	Weather Research and Forecasting

Executive Summary

Research Objective: This study aims to develop climate-informed energy system planning data and analysis tools for California by:

- + Creating a climate-informed electricity and peak-demand forecast for California from the present through mid-century that aligns with the state's decarbonization goals, as well as comparable forecasts for the other regions across the Western United States; and
- + Developing optimized electricity system portfolios that reflect future climate impacts and meet California's climate goals, evaluating resilience to climate change and incorporating climate uncertainty.

This interim report will focus on progress made on the climate-informed load forecasts developed for the study as of January 2026. Climate-informed load forecasts were developed for two policy scenarios reflecting substantially different levels of electrification: a Reference Scenario reflecting current policies as of 2024 and a Net-Zero Scenario reflecting measures from the California Air Resources Board 2022 Scoping Plan Update that results in higher electrification levels. The climate-informed load forecasts were based on the climate scenario Shared Socioeconomic Pathway (SSP) 3-7.0, and applied climate projections from four different Global Climate Models (GCMs) that were downscaled for the requisite hourly variables of interest to a high-renewables future, treating each projection as an equally plausible future. Climate-informed load forecasts accounted for impacts of increased adoption of air conditioning, as well as temperature-dependent service demand and technology efficiencies for space heating and space cooling.

The climate-informed load forecasts will serve as key inputs to the forthcoming electricity system analysis, which will develop optimized resource portfolios across the Western Electricity Coordinating Council (WECC) region, considering both scenario-based and stochastic perspectives. The forthcoming electricity system portfolios will offer insights for consideration for regionalized grid planning in a future impacted by climate change.

Key takeaways

- + All four GCMs showed a summer warming trend that will drive an increase in 1-in-10 gross load summer peak demand, ranging from 9-14% relative to the forecasts without climate impacts in the CAISO region in the forecast year 2045 as shown in Figure 1. These peak periods typically occur in the early afternoon.
- + The climate-informed load forecasts suggested that winter warming may lead to reduced electricity demand on peak winter days due to decreased space heating load. While a shift in winter months from space heating to space cooling was observed in warmer climates, the magnitude of this impact on peak winter loads relative to the impact of reduced space heating demands depended on the amount of future electric space heating. Because the Net-Zero

Scenario included higher levels of electric space heating compared to the Reference Scenario, warmer winters associated with climate change reduced winter peaks more appreciably in the Net-Zero Scenario.

- + Climate impacts on peak load may be amplified by electrification, and therefore, their impacts should be considered jointly in understanding future electricity demands.

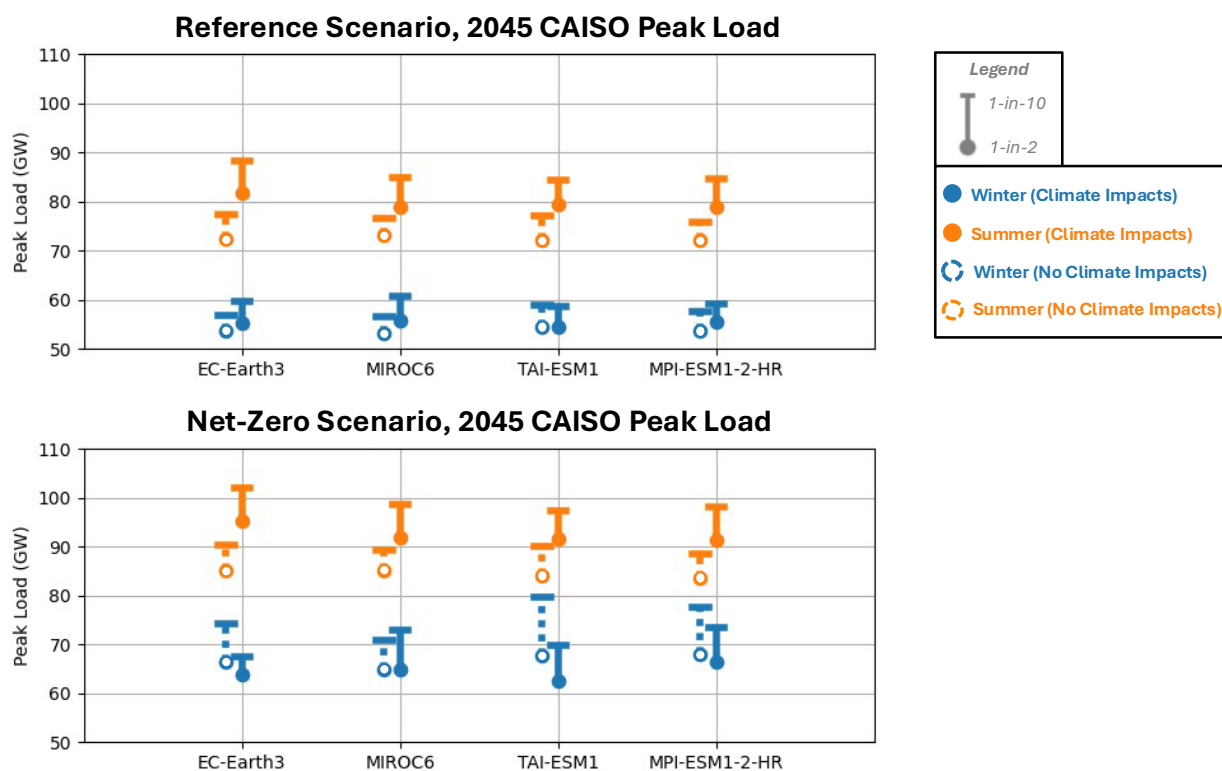


Figure 1 Seasonal 1-in-2 and 1-in-10 peak loads in the CAISO region in 2045 with and without climate impacts for Reference Scenario (top) and Net-Zero Scenario (bottom) shown for each of four GCMs (EC-Earth3, MIROC6, TAI-ESM1, and MPI-ESM1-2-HR)¹

Additional Considerations

- + There is a wide range of potential future outcomes beyond what has been evaluated in this work, which focused specifically on temperature-mediated effects on peak load based on one climate scenario (SSP3-7.0). Characterizing the probability of additional climate impacts and

¹ Summer months include June, July, and August. Winter months include December, January, and February.

associated peak demand events from other climate scenarios was outside the scope of this research.

- + While the impact of climate change on peak loads is uncertain, it is only one of many future uncertainties impacting changes in electricity demand and peak load growth in California. Other uncertainties include population and economic growth, technological change, and artificial intelligence-driven data center electricity demand, to name a few. A robust electricity resource planning exercise should ideally account for a range of plausible future outcomes when assessing future resource investment decisions.
- + The use of climate data in load forecasting and downstream electricity system planning requires careful consideration and collaboration with climate scientists, given that achieving meaningful results depends heavily on appropriate data selection and usage. Close coordination will be needed between energy system modelers, policy experts, and climate scientists to ensure that climate change is appropriately accounted for in electricity system planning. The specific choices and tradeoffs made for this study with regards to the use of climate data are discussed throughout this report.

1 Introduction

This interim report documents progress and lessons learned to-date in the California Energy Commission (CEC)-funded research project EPC-21-041, focused on “Climate-Informed Electric Grid Modeling to Support a Resilient Clean Energy Transition in California and the West.”

1.1 Background

Climate change is introducing new and complex challenges for electricity system planners. Rising temperatures and shifting weather patterns are altering both the **demand** for electricity and the **availability** of supply resources. On the demand side, higher baseline temperatures and more frequent extreme heat events are expected to increase reliance on air conditioning, accelerating adoption of cooling technologies and raising peak electricity loads.^{2, 3, 4} There is less consensus on how climate change will impact winter temperatures in California, but the projected trend suggests warmer winters as well, which may also impact electricity demands (e.g. by reducing demand for space heating).^{5, 6} On the supply side, climate change can disrupt traditional resource patterns—for

² Amonkar, Yash, et al. "Differential effects of climate change on average and peak demand for heating and cooling across the contiguous USA." *Communications Earth & Environment* 4.1 (2023): 402.

³ Zhang, Hongliang, and Shang Xu. "Climate Change, Air Conditioning Adoption, and Household Electricity Use: Evidence from the Northwestern United States." *Environmental and Resource Economics* 88.9 (2025): 2469-2501

⁴ U.S. Environmental Protection Agency. (2024). *Extreme heat*. <https://www.epa.gov/climatechange-science/extreme-heat>

⁵ Filahi, Hajar, et al. "Rising power system strains despite decreasing heating demand in a warming climate." *Scientific Reports* 15.1 (2025): 12470.

⁶ Deroubaix, Adrien, et al. "Large uncertainties in trends of energy demand for heating and cooling under climate change." *Nature communications* 12.1 (2021): 5197.

example, studies have shown that climate change is likely to impact the total and seasonal availability of hydropower across the Western U.S. and could reduce average wind resource availability.^{7, 8} Together, these shifts create a more uncertain and dynamic planning environment.

California has already experienced firsthand how climate-driven extreme events can strain the electric grid. For example, during the August 2020 heat wave, record-breaking temperatures across the Western U.S. pushed electricity demand to unprecedented levels.⁹ Simultaneously, regional supplies were constrained, contributing to rolling outages that affected hundreds of thousands of customers across California. This event highlighted the vulnerability of electricity systems to compounding stressors and underscored the need for improved resilience planning. As extreme weather events become more frequent and intense, understanding the implications of climate change is increasingly critical for electricity system planners. Consideration of climate impacts has become more commonplace across California's various electricity system planning processes including Integrated Resource Plans (IRPs), utility Climate Adaptation Vulnerability Assessment (CAVAs) and others, but the methods for incorporating climate data vary across organizations and processes as new best practices are beginning to emerge and evolve.

1.2 Project Overview

This study aims to **develop climate-informed energy system planning data and analysis tools for California**. Towards this research objective, this study:

- + Creates a climate-informed electricity energy & peak demand forecast from now to mid-century for California which also meets the state's decarbonization goals, as well as forecasts for the other regions in the Western Electricity Coordinating Council (WECC);
- + Develops optimized electricity system portfolios reflecting future climate impacts and that meet California's climate goals, evaluating resilience to climate impacts and incorporating climate uncertainty; and
- + Will provide insights and lessons learned from incorporating advanced climate data and modeling techniques to inform climate-resilient grid planning.

The project team was led by Energy and Environmental Economics, Inc. (E3) with support from Eagle Rock Analytics in the use and application of climate data, and in developing climate-informed hydropower and renewable generation profiles. Lawrence Berkeley National Laboratory (LBNL) also performed interviews with stakeholders regarding the use of climate informed data in California resource planning, and developed code enhancements of the electricity sector production simulation model (RESOLVE), which will be discussed in a separate report.

⁷ Szinai, Julia K., et al. "Climate change and its influence on water systems increases the cost of electricity system decarbonization." *Nature Communications* 15.1 (2024): 10050.

⁸ Chen, Liang. "Impacts of climate change on wind resources over North America based on NACORDEX." *Renewable energy* 153 (2020): 1428-1438.

⁹ California Independent System Operator, (2021). "Root Cause Analysis: Mid-August 2020 Extreme Heat Wave". <https://www.caiso.com/Documents/Final-Root-Cause-Analysis-Mid-August-2020-Extreme-Heat-Wave.pdf>

This interim report focuses specifically on the climate-informed load forecasts that have been developed as of January 2026. Results from the optimized electricity system modeling will be included in the forthcoming final report.

2 Climate-Informed Planning in California

In California, key stakeholders have long recognized the need to consider climate change in electric system planning. The California Public Utilities Commission (CPUC) brought climate adaptation matters to the forefront in 2018 with R.18-04-019, “Order Instituting Rulemaking to Consider Strategies and Guidance for Climate Adaptation.” With Decision 19-10-054 in 2019, the CPUC adopted an official definition of climate change adaptation pertaining to energy utilities, and provided initial guidance for the use of tools, models, and data for incorporating climate change into utility planning.¹⁰ This set in motion ongoing efforts to embed climate change considerations into California’s electricity system planning.

California’s electricity system planning efforts are divided across many key stakeholders, each with distinct roles to play, as summarized in Table 1.

“Climate change adaptation is adjustment in natural and human systems to a new or changing environment. Adaptation to climate change for energy utilities regulated by the Commission refers to adjustment in utility systems using strategic and data-driven consideration of actual or expected climatic impacts and stimuli or their effects on utility planning, facilities maintenance and construction, and communications, to maintain safe, reliable, affordable and resilient operations.”

CPUC Decision 19-10-054

¹⁰CPUC Decision 19-10-054, “Decision on Phase 1 Topics 1 and 2”, 10/24/2019.
<https://docs.cpuc.ca.gov/PublishedDocs/Published/G000/M319/K075/319075453.PDF>

Table 1 Summary of California long-term electricity system planning workstreams across organizations¹¹

Organization	Activity/Product	Frequency	Key Outputs	Look-Ahead
California Energy Commission (CEC)	Integrated Energy Policy Report, Forecasts and System Planning	Biennial for full report, with annual updates	Hourly demand scenarios and peak forecasts	20 years
California Public Utilities Commission (CPUC)	Integrated Resource Plan (IRP) & Long-term Procurement	Biennial	System plans that meet greenhouse gas, reliability, and cost objectives	10 years for reliability, approximately 20 years for planning portfolios
California Independent System Operator (CAISO) & CPUC	Transmission Planning Process	Annual	Identify transmission needs	10 & 15 years
Load Serving Entities (LSEs)	Integrated Resource Plan (IRP), Risk Assessment Mitigation Phase (RAMP), and Climate Adaptation and Vulnerability Assessments (CAVA)	IRP: Biennial RAMP and CAVA: every 4 years	Procurement needs, risk and climate impacts on infrastructure	IRP: 20 years RAMP: tied to General Rate Case test year period CAVA: uses a Global Warming Level approach for look-ahead (2°C and 2.5°C)

Each piece of the electricity system planning puzzle may present different opportunities for incorporating climate impacts. For example:

- + The CEC develops the Integrated Energy Policy Report (IEPR) California Energy Demand forecast where downscaled climate data is incorporated.¹² The IEPR demand forecast is used by state agencies and utilities in integrated resource planning, as well as in the transmission planning process and 20-year transmission outlook.
- + In the CPUC IRP process, the CPUC ingests climate impacts on loads from the CEC IEPR.

¹¹ Table adapted from research performed under this grant by Liyang Wang, LBNL.

¹² California Energy Commission, Adopted 2024 Integrated Energy Policy Report Update.
<https://efiling.energy.ca.gov/GetDocument.aspx?tn=266416>

- + California energy utilities are required to file a Climate Adaptation and Vulnerability Assessment (CAVA) every four years focused on climate risks to utility operations, which are subject to the CPUC’s guidance on incorporating climate data. The impacts considered in utility CAVAs extend beyond temperature changes to supply and demand (e.g. extreme storms and flooding, sea-level rise, and wildfire), and the assessment covers a wide range of utility infrastructure.

The CPUC has continued to iterate on guidance provided around the recommended approaches for incorporating climate impacts. For example, in Decision 24-08-005, the CPUC adopted refinements to their original guidance, adopting a specific greenhouse gas scenario—Shared Socioeconomic Pathway (SSP) 3-7.0—to be used as the reference scenario for utilities in their CAVAs and also recommended this scenario for use in other proceedings (e.g. for long-term infrastructure planning).¹³ The Decision also adopted a Global Warming Level (GWL) approach as the basis for CAVA planning and recommended that utilities consider a GWL approach in other proceedings.

The present study is focused specifically on incorporating climate impacts into load forecasts and generation resource planning. However, as shown in Figure 2, this is just one component of the broad set of efforts that flow into electricity system planning in California.

¹³ CPUC Decision 24-08-005, “Phase 2 Decision Updating Climate Change Adaptation Modeling Requirements and Refining the Climate Adaptation and Vulnerability Assessments”, 8/1/2024.
<https://docs.cpuc.ca.gov/PublishedDocs/Published/G000/M537/K988/537988980.PDF>

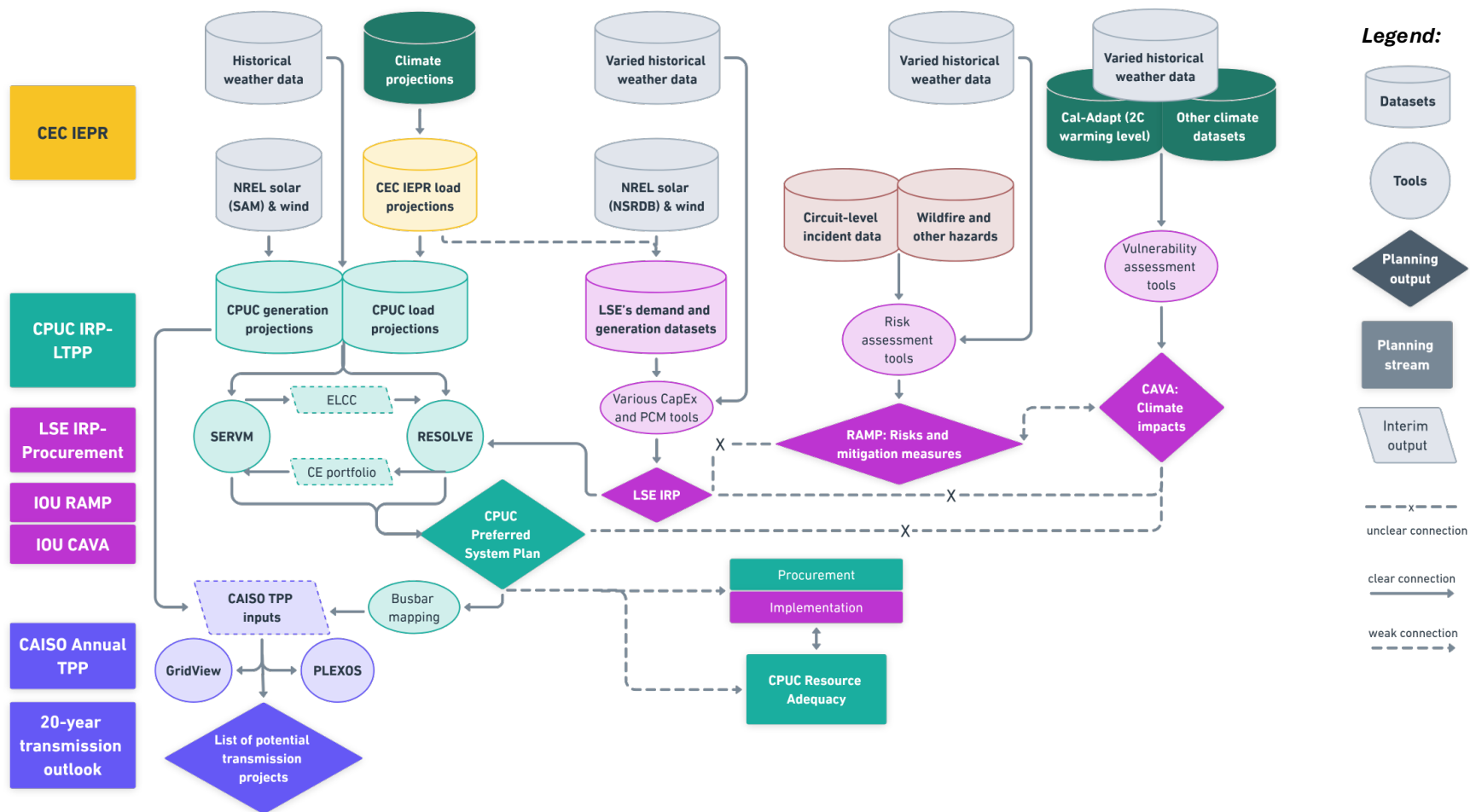


Figure 2 Flow diagram illustrating how climate data flows throughout various electricity system planning processes in California¹⁴

¹⁴ Flow chart adapted from research performed under this grant by Liyang Wang, LBNL.

3 Climate Dataset and Scenarios

3.1 Climate Data

This study uses climate data made available by the Cal-Adapt: Analytics Engine (Analytics Engine), which is an open-source data platform designed to aid in analytics for California’s electricity sector. The Analytics Engine offers a wide array of datasets for use in analysis, including downscaled datasets from fifteen distinct Global Climate Models (GCMs). The GCMs are all part of the most recent Coupled Model Intercomparison Project, Phase 6 (CMIP6), an international effort across research institutions to produce climate model outputs with consistent standards.¹⁵ The Analytics Engine offers downscaled climate datasets produced using two different downscaling approaches: dynamical downscaling using the Weather Research & Forecasting Model (WRF), and hybrid-statistical downscaling using the Localized Constructed Analogs version 2 (LOCA2-Hybrid). As described in the Analytics Engine Data Catalog, WRF was applied to eight GCMs from the CMIP6 ensemble, and the LOCA-2 hybrid methodology was applied to fifteen GCMs from the CMIP6 ensemble, resulting in a total of twenty-three downscaled datasets available on the Analytics Engine.¹⁶

As discussed in the Analytics Engine guidance documentation, there are tradeoffs between the different climate datasets which impacted the selection of data for this study.¹⁷ While the LOCA2-Hybrid datasets are available for a wider range of GCMs, this data is only available at a **daily** temporal resolution, involves a more limited set of variables (excluding many of interest to a high-renewable grid), and is limited to the California domain. By contrast, the WRF datasets comprise fewer GCMs but provide **hourly** temporal resolution, include many more variables (including some of particular interest to a high-renewable grid), and extend across the Western region (thus enabling WECC-wide analysis). The hourly resolution, more comprehensive suite of variables, and broad geographic coverage offered by the WRF datasets was determined to be more appropriate for use in this study for evaluating hourly impacts on loads (as well as impacts on electricity supply in forthcoming analysis) across the Western Interconnection. The WRF datasets also provide dynamically consistent variables, meaning that for a given point in time and space, the different variables within each dataset are internally consistent and obey the laws of physics. Dynamic consistency is important for consideration of compound as well as cascading climate impacts that depend on interaction of multiple variables across space or time. In the present study, dynamic consistency was desirable for maintaining realistic interactions between variables impacting electricity supply and variables impacting electricity demand. For these reasons, the WRF datasets were deemed more appropriate for use in the current study rather than the LOCA2-Hybrid datasets.

¹⁵ Analytics Engine Guidance Glossary. <https://analytics.cal-adapt.org/guidance/glossary/#cmip6>

¹⁶ Analytics Engine Data Catalog. <https://analytics.cal-adapt.org/data/catalog/>

¹⁷ Analytics Engine, Guidance on Using Climate Data in Decision Making. https://analytics.cal-adapt.org/guidance/using_in_decision_making/

Of the available WRF datasets, further differences impacted which were most appropriate for the analysis in this study. In particular, there are differences in the bias correction across the various WRF datasets available from the Analytics Engine. As noted in the Analytics Engine guidance, the *a priori* bias-corrected models are likely more appropriate for use in energy sector analysis.¹⁸ Out of the available 8 GCMs that were downscaled using WRF, only five had *a priori* bias correction. Four out of these five WRF datasets were chosen for use in this study.¹⁹ The final selected datasets were downscaled projections (using WRF) from the four GCMs listed below:

- EC-Earth3
- MIROC6
- TAI-ESM1
- MPI-ESM1-2-HR

The different GCMs take different approaches to modeling the physics that influence climate. All GCMs available on the Analytics Engine have been pre-selected based on their ability to capture dynamics specific to extreme weather in California, but they vary with respect to how well they represent high-priority variables of interest for California (e.g. extreme precipitation, Santa Ana winds, El Niño Southern Oscillation, etc.), as well as in their sensitivity to atmospheric greenhouse gas (GHG) concentrations (i.e. the amount of warming that results from a given amount of GHG).²⁰ Each of the four chosen downscaled GCMs was treated as an equally-plausible future in this study. The climate-informed load forecasts leveraged hourly temperature data from these four downscaled GCMs at a 3 km spatial resolution within California and a 9 km spatial resolution across the rest of the WECC.

3.2 Climate Scenarios

There is a substantial uncertainty in how much the climate will change in the future, which will be highly dependent on cumulative concentrations of greenhouse gas emissions and other global factors. Given this uncertainty, different climate scenarios are defined by the Intergovernmental Panel on Climate Change (IPCC) to represent various plausible futures based on global trends called Shared Socioeconomic Pathways (SSPs). The Cal-Adapt: Analytics Engine offers datasets for three distinct SSPs: SSP2-4.5, SSP3-7.0, and SSP5-8.5, as described in the table below reproduced from the Cal-Adapt: Analytics Engine guidance:

¹⁸ Analytics Engine Guidance, “Using Climate Projections in the Analytics Engine”. https://analytics.cal-adapt.org/guidance/using_in_decision_making/guidelines/

¹⁹ EC-Earth3-Veg was not selected for use in this study because it lacked hourly hub-height wind data which was required for the analysis.

²⁰ Krantz et al., 2021, “Memorandum on Evaluating Global Climate Models for Studying Regional Climate Change in California”. https://www.energy.ca.gov/sites/default/files/2022-09/20220907_CDAWG_MemoEvaluating_GCMs_EPC-20-006_Nov2021-ADA.pdf

Table 2 Three of the common greenhouse gas trajectory scenarios hosted on the Analytics Engine²¹

Emissions Trajectory	Definition	Description	Outcome
SSP2-4.5	4.5 watts per meter squared of radiative forcing in the year 2100	Emissions continue at present levels to mid-century and then decline	2.7°C warmer at end of century
SSP3-7.0	7.0 watts per meter squared of radiative forcing by the year 2100	Emissions roughly double from current levels by 2100	3.6°C warmer at end of century
SSP5-8.5	8.5 watts per meter squared of radiative forcing by the year 2100	Emissions roughly double from current levels by 2050	4.4°C warmer at end of century

In this study, only SSP3-7.0 is considered. This is primarily because the CPUC adopted SSP3-7.0 as the reference scenario for electricity and gas investor-owned utilities (IOUs) to use in utility CAVAs, and has also recommended it for other relevant use-cases.²² Therefore, SSP3-7.0 was selected as the core climate scenario to evaluate in this study to make the resulting analysis the most directly applicable to electricity sector planners in California. Notably, SSP3-7.0 is only one of many plausible futures depending on future conditions, and it is more moderate than other scenarios such as SSP5-8.5. While selecting a single SSP climate scenario to focus on may allow for more targeted results for use in planning, it also limits the range of outcomes that are considered.

In recent years, climate impact assessments have increasingly adopted a Global Warming Level (GWL) approach rather than a time-slice approach.^{23, 24} Under a GWL framework, impacts are evaluated at a specified level of global warming relative to pre-industrial conditions. The CPUC has recommended that utilities consider phasing in the use of a GWL approach²⁵; however, the present study, like many planning processes, is explicitly framed in terms of time. This limits the relevance of a GWL framework, which aims to remove time as a variable. Focusing on a fixed future time window for climate data (e.g. weather years drawn from 2030–2060 climate data) allows for a more straightforward integration of climate impacts with the timing of electrification across policy scenarios. Moreover, several key advantages of a GWL approach are not particularly relevant for this application. For example, GWLs help address variation across GCMs in the timing of when specific

²¹Table reproduced from Analytics Engine, About Climate Projections and Models. https://analytics.cal-adapt.org/guidance/about_climate_projections_and_models/

²²CPUC Decision 24-08-005, “Phase 2 Decision Updating Climate Change Adaptation Modeling Requirements and Refining the Climate Adaptation and Vulnerability Assessments”, 8/1/2024. <https://docs.cpuc.ca.gov/PublishedDocs/Published/G000/M537/K988/537988980.PDF>

²³Analytics Engine Guidance on Using Climate Data in Decision-Making. https://analytics.cal-adapt.org/guidance/using_in_decision_making/

²⁴See here for additional explanation on GWL approach. <https://www.climatechangeinaustralia.gov.au/en/changing-climate/future-climate-scenarios/global-warming-levels/reaching-global-warming-levels/>

²⁵CPUC Decision 24-08-005, “Phase 2 Decision Updating Climate Change Adaptation Modeling Requirements and Refining the Climate Adaptation and Vulnerability Assessments”, 8/1/2024. <https://docs.cpuc.ca.gov/PublishedDocs/Published/G000/M537/K988/537988980.PDF>

warming thresholds are reached, enabling the inclusion of a broader set of models such as those (“hot models”) that appear to warm too quickly but may be useful in portraying of dynamics that are important to address. Another benefit of adopting the Global Warming Level (GWL) approach is that one does not necessarily need to make an assumption about Shared Socioeconomic Pathways (SSPs), which allows for including more CMIP simulations from multiple SSP scenarios to enhance uncertainty quantification. However, the selection of GCMs was already constrained for other reasons as described in Section 3.1 (i.e. requiring bias-corrected models with high temporal and spatial resolution with dynamically consistent variables). Given these considerations, this study did not take a GWL based approach as there was minimal practical benefit to its inclusion.

3.3 Climate Data Preprocessing for Use in Demand Forecasts

3.3.1 Population Weighting

Since this analysis was specifically focused on estimating the impacts of climate-informed weather data on future electricity demand, the project team used the gridded climate data described in Section 3.1 to generate regional population-weighted data for use in the climate-informed demand forecasts. This step was taken to ensure that climate inputs were reflective of the locations where people live and work (i.e. co-located with electricity demand for space heating and space cooling) rather than reflecting locations that would have little relevance to electricity demand. While improved accuracy could have been achieved using a floor-area weighted approach, this would have significantly increased the complexity of the process. To strike a balance between amount of data processed, and accuracy of results, the population center approach was deemed an adequate middle ground. To calculate population-weighted hourly load profiles, temperature data was pulled for the centroid of each of the largest census defined ‘places’ within a county. This temperature data was then fed into our hourly load shaping models producing load profiles for all weather conditions at each individual place. The place-level hourly loads were then aggregated to the regional level using a population-weighted mean. The end result of this process was a set of hourly load profiles for each region, driven by location-specific temperature.

3.3.2 Alignment with Historical Temperature Records

In developing the climate-informed load forecasts, there were many possible options for representing current or historical climate conditions.²⁶ Initially, the project team considered using the ERA5 reanalysis dataset for this purpose.²⁷ However, collaborating climate scientists recommended instead using data for historical years from each of the GCMs for better consistency between historical and future climate signals.²⁸ Utilizing the downscaled GCM data for historical

²⁶ Analytics Engine Data Catalog. <https://analytics.cal-adapt.org/data/catalog/>

²⁷ ERA5 data refers to the ECMWF reanalysis data V5 at a 0.25 degree latitude/longitude grid.

²⁸ Climate scientists were engaged through CEC grant number EPC-21-037, “Climate-Informed Generation Capacity Modeling to Support a Climate Resilient Transition to a Clean Electricity System,” Eagle Rock Analytics, Inc.

years required careful processing given that some of the downscaled data over the historical period deviates from actual observed historical weather distributions in ways that were important for this study, especially in winter and during cold snaps, as demonstrated by Figure 3. Specifically, in the northwestern region of the WECC (denoted WECC_NW in this report), some of the GCMs showed extreme cold temperatures far beyond anything in the historical distribution of temperatures for the region. Some counties were portrayed by GCMs as having cold snap temperatures 20°F below their observed historical minimum temperatures for the past 80 years. To address this, E3 post-processed the GCM-derived historical temperature data in the northwestern region by clipping the temperature within a county to its historical minimum temperature based on ERA5 data with an aim to maintain the trend of the temperature data while ensuring that it stayed within the realm of realistic temperatures. Specifically, the clipping was applied such that in any hour, if the temperature from the WRF model was below the ERA5 county level minimum, it was modified to be set to the county level minimum instead.

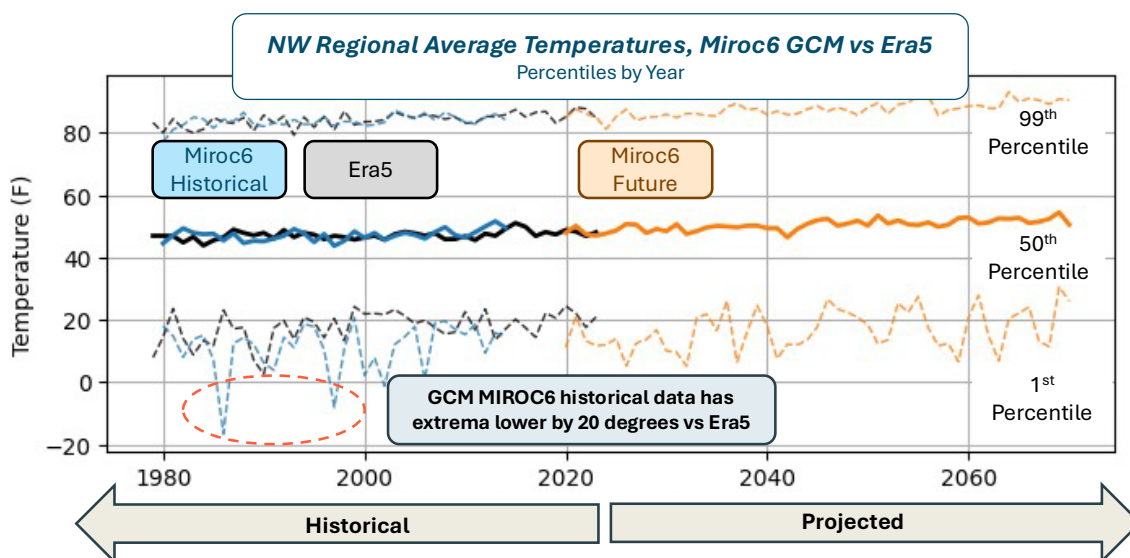


Figure 3 Regional average temperature comparison between downscaled MIROC6 GCM and ERA5 reanalysis data for WECC_NW region

4 Climate-Informed Demand Forecast Methodology

In this study, load forecasts were developed for two distinct policy scenarios with substantially different levels of electrification (e.g. in buildings and transportation):

1. **Reference Scenario**, representing current policy as of 2024; and
2. **Net-Zero Scenario**, which aligns with the policies outlined in the California Air Resources Board 2022 Scoping Plan within California to meet the state's greenhouse gas emissions

targets.²⁹ For regions outside of California, this scenario assumes that states that have committed to achieving net-zero greenhouse gas emissions by 2050 are on a net-zero trajectory, while all other states remain on the Reference Scenario trajectory, as shown in Table 3. The Net-Zero scenario includes substantially more electrification than the Reference Scenario.

Table 3 Policy assumptions by scenario for states modeled across the West³⁰

State	Reference Scenario	Net-Zero Scenario
Arizona	Reference Policies	Net Zero Policies
Colorado	Reference Policies	Net Zero Policies
California	Reference Policies	Net Zero Policies
Idaho	Reference Policies	Reference Policies
Montana	Reference Policies	Reference Policies
Nevada	Reference Policies	Reference Policies
New Mexico	Reference Policies	Net Zero Policies
Oregon	Reference Policies	Net Zero Policies
Utah	Reference Policies	Reference Policies
Washington	Reference Policies	Net Zero Policies
Wyoming	Reference Policies	Reference Policies

Detailed policy assumptions and scenario inputs are described in Appendix A. Both policy scenarios were evaluated with and without climate impacts to allow for the impacts of climate change on future electricity demand to be isolated and evaluated. The climate-informed load forecast included impacts from increased adoption of air conditioning due to rising temperatures, as well as impacts to technology efficiencies and demand for space heating and space cooling.

This section describes the methodology for developing the baseline load forecasts without climate impacts, as well as the methodology for incorporating climate impacts to achieve the final climate-informed hourly load forecasts.

²⁹ 2022 Scoping Plan for Achieving Carbon Neutrality, California Air Resources Board.
<https://ww2.arb.ca.gov/sites/default/files/2023-04/2022-sp.pdf>

³⁰ Note that the scenario naming convention has been updated for the final report for this project relative to the names used in this interim report.

4.1 Baseline Load Forecasting with No Climate Impacts

4.1.1 Annual Energy Demand Modeling

To develop baseline load forecasts without climate impacts, annual electricity demands from 2022-2050 were first modeled using E3's PATHWAYS model, which is a bottom-up stock rollover model that accounts for stocks and resulting energy demands across all sectors of the economy.³¹ The PATHWAYS model captures “infrastructure inertia” reflecting realistic timing of replacing vehicles, appliances, and other infrastructure. The PATHWAYS model calculates economy-wide energy demand based on the infrastructure operating in each year, as well as input assumptions for technology efficiencies and service demands. While PATHWAYS accounts for technology-driven total annual energy efficiency trends, additional temperature-dependent efficiency effects are incorporated in the hourly models, discussed in section 4.1.2. Base year 2022 electricity and natural gas demands were benchmarked to historical actuals reported in the California Energy Commission Integrated Energy Policy Report (IEPR) for the state of California. All other 2022 energy demands (i.e. energy demands for fuels other than natural gas and electricity in California, and all energy demands outside of California) were benchmarked to historical actual 2022 data from the U.S. Energy Information Administration State Energy Data System (EIA SEDS).

4.1.2 Hourly Load Modeling

Hourly load forecasts were developed using a suite of load shaping tools designed to capture hourly loads for specific end-uses, starting with the annual electricity demands as an input. Separate hourly load shaping tools were used for baseload, incremental transportation electrification loads, and incremental building electrification loads – specifically space heating, space cooling, and water heating.³² To ensure base-year alignment with historically-observed electricity demands, hourly loads were benchmarked to the 2022 base-year. This benchmarking was performed by feeding 2022 temperature data from the ERA5 model³³ through the hourly load shaping tools and then normalizing the output load profiles such that hourly loads across the 8760 hours in the 2022 base-year summed to 1. This normalization process ensured that when the annual electricity demand from PATHWAYS for the 2022 base-year was multiplied by the normalized hourly load profiles, the sum of the hourly loads was equal to the actual historical 2022 annual electricity demand. Hourly loads for all modeled weather years were then normalized in reference to the 2022 base-year, as shown in the equation below:

$$Annual\ load_{weather\ year\ i} = (PATHWAYS\ Annual\ Load) \left(\frac{\sum_{hour=1}^{8760} hourly\ load_{weather\ year\ i}}{\sum_{hour=1}^{8760} hourly\ load_{2022}} \right)$$

³¹ E3 Tools: PATHWAYS. <https://www.ethree.com/tools/pathways-model/>

³² Incremental loads were measured relative to 2022 annual electricity demands for each end-use.

³³ ERA5 data refers to the ECMWF reanalysis data V5 at a 0.25 degree latitude/longitude grid.

This normalization approach ensures that when the PATHWAYS annual load outputs are combined with the outputs from the hourly load shaping tools, the resulting temperature-dependent hourly loads maintain inter-annual load differences for modeled weather years in reference to the 2022 base-year as temperatures vary. In other words, total annual cooling loads will be higher in a hotter year, relative to a colder one.

Load shapes for baseloads were calculated using a neural network model designed to simulate weather-driven load shapes over a multi-decadal period. The neural network was trained using a sample of historical load and weather data, and benchmarked to fit existing correlations between weather and load. A quantile mapping approach was used in regions where the neural network model was unable to extrapolate to future climate weather conditions outside of the range of the training data. In these cases, interim neural network outputs showed a lessening impact of temperature on loads as temperature increased outside of the training data range. The quantile mapping technique remaps the input temperature data to fall within the range of historical temperatures resulting in a more performant output load distribution when comparing across temperatures. The quantile mapping primarily serves to ensure that the final hourly loads behave appropriately, while preserving the magnitude of the total annual energy forecast. The application of quantile mapping was not needed in regions where the neural network was able to predict a reasonable temperature-dependent relationship across all temperature inputs (i.e. when the predictions did not require extrapolation beyond the training dataset).

Transportation electrification load shapes were developed using a bottom-up model that combines driver survey data and utility-specific data with the latest technology and behavioral insights to develop hourly load shapes associated with various charging management strategies. The bottom-up model starts with a statistically robust sample of driving patterns for a vehicle class using a Markov Chain Monte Carlo sampling process of vehicle trip data. Charging decisions for hundreds of drivers are simulated based on the availability of chargers in various locations, vehicles' charging needs, electricity rates, and managed charging strategies.

Building electrification loads for space heating, space cooling, and water heating were calculated by modeling heating and cooling demands as functions of outdoor air temperatures based on the type of heating or cooling device and its Coefficient of Performance (COP). The underlying device-agnostic end-use service demand is calculated using a piece-wise relationship between temperature and load, assuming that the demand is zero for temperatures at which there is no heating/cooling demand, and is linear beyond the temperature at which heating/cooling demand begins. The linear relationship is calibrated such that the regional aggregate loads match historical benchmarks of annual, monthly, and peak loads. Device-specific loads are then calculated by applying a temperature-driven COP profile to the end-use service demand. The building electrification hourly load calculation was run at county-level spatial granularity, providing temperature-dependent hourly load shapes at the county level. To ensure that the model produced reasonable results, it was benchmarked to historical actuals for each region modelled using datasets from EIA, historical utility loads & reports, and NREL's ComStock & ResStock models.^{34, 35} For the baseline building electrification and baseload hourly loads without climate impacts, the

³⁴NREL ComStock. <https://comstock.nrel.gov/>

³⁵NREL ResStock. <https://resstock.nrel.gov/>

“historical” weather data from each of the four GCMs were used as inputs. Each GCM was inputted into the model separately, providing four timeseries profiles without climate impacts (i.e. representing historical weather). For the baseline load forecasts without climate impacts, each forecast year included 33 distinct weather years – years 1981-2013 from the timeseries temperature data for each GCM.

4.2 Incorporating Climate Impacts

Three primary effects of changing temperature due to climate change were identified and modeled as part of the climate-informed load forecasts:

1. Increased adoption of air conditioning due to rising temperatures;
2. Changes to service demand for heating and cooling due to changing temperatures (i.e. changes to how much space heating, air conditioning, and water heating are used across the population); and
3. Changes to device efficiency for heaters and air conditioners due to changes in temperature.

These climate impacts were incorporated in the modeling as described below.

4.2.1 Modeling Increased Air Conditioning Adoption

The climate-informed load forecasts account for estimated increases in air conditioning adoption due to rising temperatures. Future air conditioning adoption was predicted using a logistic regression model. The logistic regression model was trained on historical air conditioning adoption data from the Residential Appliance Saturation Study (RASS) data from the CEC, combining survey data from the 2003, 2009, and 2019 vintages of the study to create a larger input dataset. The input data for the logistic regression included:

1. Whether or not a household had air conditioning based on the RASS; and
2. Historical Cooling Degree Days (CDDs) over a 5-year period (e.g., CDDs from 2014 through 2018 for the year 2019) for the climate zone that the household resided in, using the population weighting approach described in Section 3.3.1.

CDDs were calculated relative to a standard temperature of 65°F. Temperature data for CDD calculation was pulled from the Cal-Adapt: Analytics Engine for each city in California and averaged across the climate zone weighted by the city population. Standard validation metrics were calculated to evaluate the predictive capability of the logistic regression model on an unseen test dataset. Model performance metrics are shown in Table 4.

Table 4 Model Performance Metrics for the AC Adoption Logistic Regression Model

Model Performance Metric	Score
Accuracy	0.69
Precision	0.71
Recall	0.86
F1 Score	0.78
Area Under the Curve (AUC)	0.71

Within California, the logistic regression was applied to each county across the state and benchmarked to 2019 saturation levels from the RASS data to predict future levels of air conditioning adoption. For the states outside of California, the logistic regression was applied at the state level. Temperature data to calculate the annual CDDs for WECC states were also pulled from the Analytics Engine for each county and averaged by the county population. Future air conditioning adoption predictions for WECC states were benchmarked to 2022 levels. Note that the same percentage increases in air conditioning adoption were applied across the residential and commercial sectors.

The climate-informed load forecasts modeled an increased number of air conditioning devices operating in future years based on the temperature data from each GCM. Figure 4 shows an example of the predicted increase in levels of air conditioning adoption across California for 2050 relative to 2020 using climate data from the MIROC6 GCM. Note that for regions displayed in gray, there was not enough data to predict changes in future adoption.

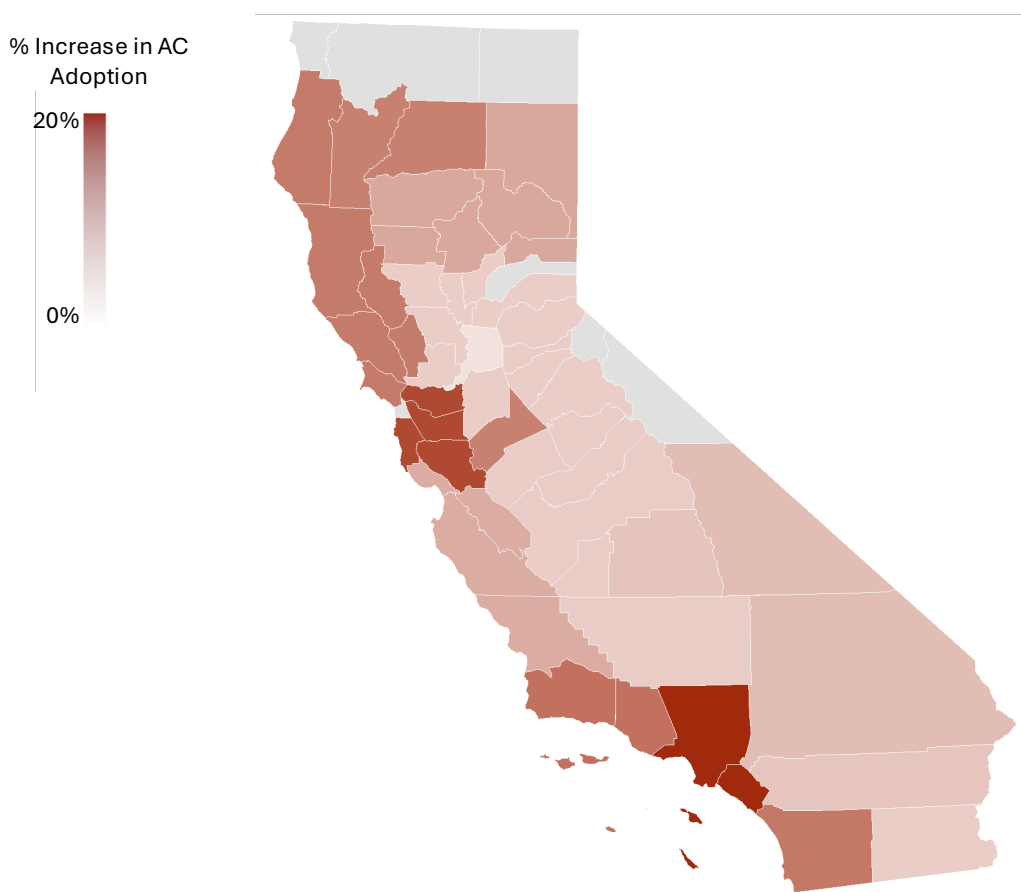


Figure 4 Percent increase in air conditioning adoption in 2050 relative to 2020 using downscaled MIROC6 GCM data

4.2.2 Modeling Climate Impacts on Service Demand and Technology Efficiencies

As previously described in Section 4.1.2, the hourly building electrification load model takes hourly outdoor air temperature as a direct input, and the impact of temperature on both service demand and device efficiency for heating and cooling devices are captured innately in the model. Population-weighted county level hourly outdoor air temperature was derived from each of the downscaled GCMs (as described in Section 3.3.1) and used as an input to calculate temperature-dependent hourly space heating, space cooling, and water heating loads. The approach for

Figure 5 shows an example of the annual aggregate impacts of temperature on service demand (left) and device efficiency (center), and the final combined impact (right) across the CAISO region for the downscaled EC-Earth3 GCM calculated from the final hourly space heating and space cooling loads.

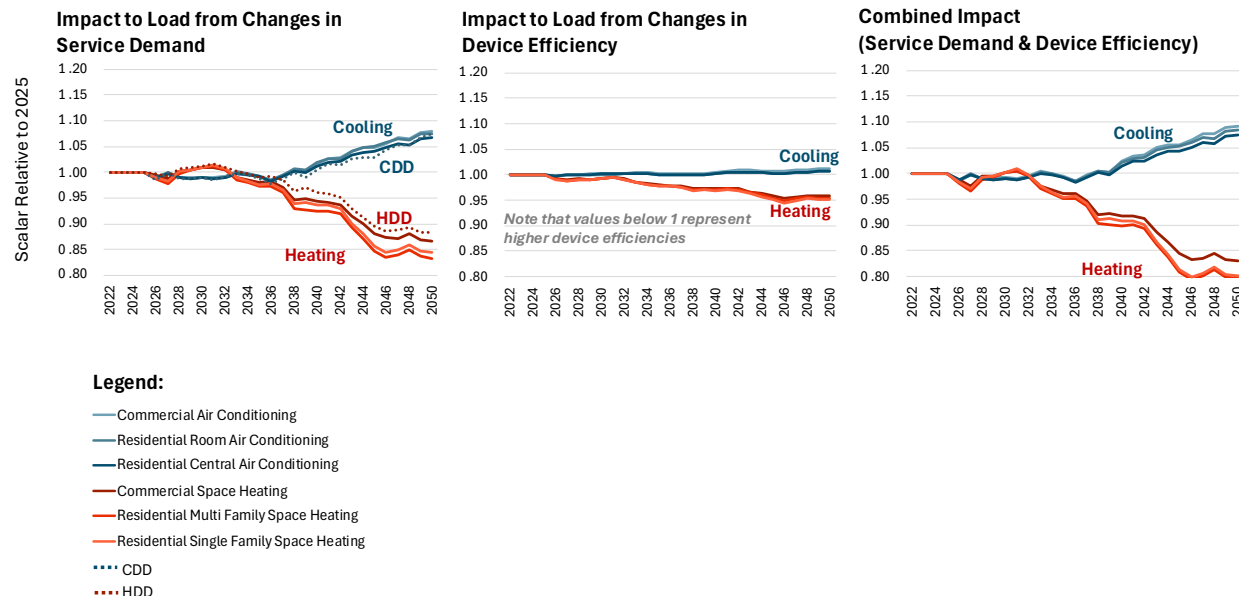


Figure 5 Example of climate impacts on heating and cooling service demands (left) and device efficiencies (center), as well as combined impact (right). Data is shown for California using downscaled EC-Earth3 data³⁶

As previously described in Section 4.1.2, future climate data from the downscaled GCMs was fed into a neural network model to develop temperature-dependent hourly baseloads. Together, the incremental building electrification loads and the baseloads from the baseload neural network model comprised the components of hourly loads that accounted for climate impacts. Similar to the methodology used in developing baseline load forecasts without climate impacts, each of the four GCM-derived datasets was fed into the hourly load models separately, producing four separate timeseries. The 2045 forecast year of the climate-informed load forecast utilized in downstream modeling efforts included 31 distinct weather years within a +/-15 year range of the forecast year (e.g. GCM data from the years 2030-2060). Using a range of weather years (e.g. 30 different weather years) is standard practice in load forecasting to capture interannual variability. The climate-informed load forecasts specifically used future weather years (2030-2060) as opposed to historical weather years (e.g. 1981-2013 weather years were used to develop the baseline forecast without climate impacts, as described in Section 4.1).

³⁶ Future changes in cooling degree days (CDD) and heating degree days (HDD) are also shown relative to 2022 levels for reference

5 Resulting Climate Impacts on Peak Loads

5.1 Climate Impacts on Peak Loads in the CAISO Region

The core driver of differences between the load forecasts with climate impacts and the load forecasts without climate impacts is the fact that modeled future temperatures across California are notably different than historical temperatures. This has been observed in other studies focused on electricity demands in California. For example, a CEC analysis found that a 1-in-27 year heat event based on a 30-year time history became a more frequent 1-in-14 year heat event when truncating the time history to 20 years.³⁷ Figure 6 shows a comparison of the modeled daily high temperatures in June-August for historical years (1981-2013) compared to the 2045 forecast year for the downscaled GCMs used in this study.

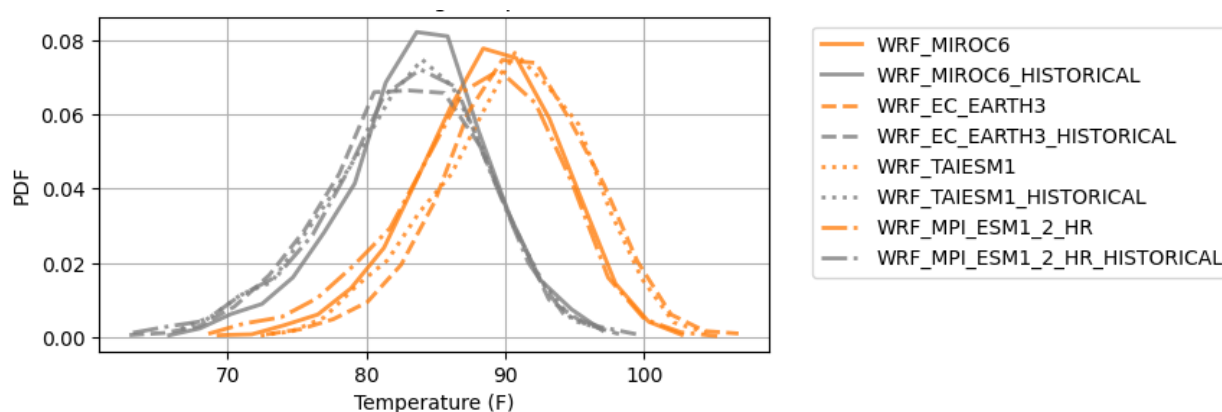


Figure 6 Distribution of daily California statewide maximum population weighted-average daily high temperatures for June through August for each downscaled GCM for historical years (gray) and for 2045 forecast year (orange)

Figure 7 shows the 1-in-2 and 1-in-10 peak loads for the CAISO with and without climate impacts in 2045. Summer peaks are shown in orange, and winter peaks are shown in blue. For results shown in this report, “summer” months include June, July, and August, while “winter” months include December, January, and February.³⁸ All of the models agree that there is a summer warming trend that will drive an increase in summer peak electricity demand. Across the four downscaled GCMs tested, the 1-in-10 summer peak increased by 6.3-10.1 GW in the Reference Scenario and 7.5-10.3 GW in the Net-Zero Scenario. The directional impact of climate on summer peaks was clear across GCMs, leading to an increased summer peak across models. However, the resulting climate impacts

³⁷ California Energy Commission, (2023). “Commission Report - Diablo Canyon Power Plant Extension - Final Draft CEC Analysis of Need to Support Reliability”. <https://efiling.energy.ca.gov/GetDocument.aspx?tn=248971>

³⁸ Note that it is possible that some regions considered in this study may experience extreme heat days outside of the June-August window (e.g. in September). While all months of the year will be included in the downstream electric sector analysis for the project and the corresponding final report, the results presented in this report are shown for brevity and ease of comparison.

on winter peaks are more variable across the different GCMs. In the Reference Scenario, climate impacts lead to a modest increase in winter peak demands. However, in the Net-Zero Scenario, three of the four GCMs (EC-Earth3, TAI-ESM1, and MPI-ESM1-2-HR) led to a decreased winter peak.

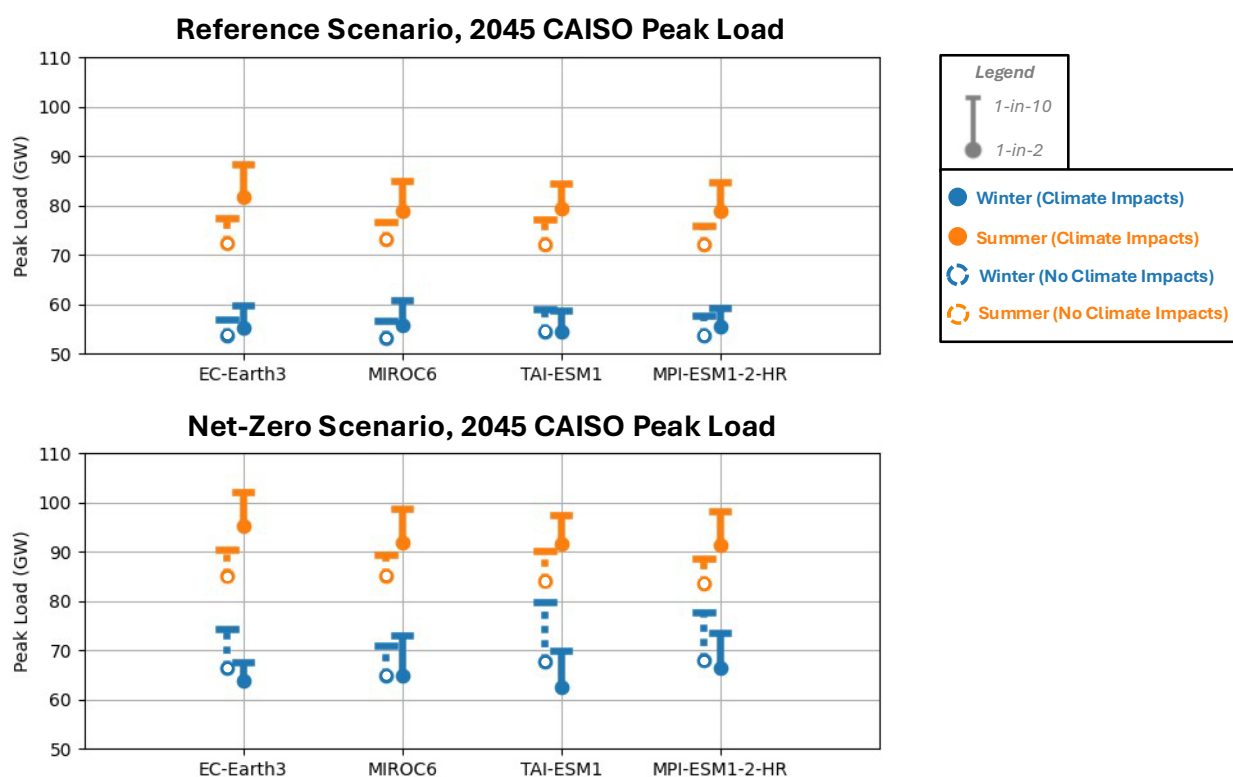


Figure 7 Seasonal 1-in-2 and 1-in-10 peak loads in CAISO region in 2045 with and without climate impacts for Reference Scenario (top) and Net-Zero Scenario (bottom)

The direction and magnitude of the climate impacts on the winter peak are heavily dependent on the penetration of electric space heating. In the Reference Scenario, there is limited penetration of electric space heating. Warmer winters lead to increases in air conditioning demands in winter hours, which result in higher winter peaks, and with limited penetration of electric space heating, there is minimal peak load reduction from the winter warming. However, in the Net-Zero Scenario, there is a high penetration of electric space heating. In this case, the warmer winters lead to a reduction in space heating demand compared to winters based on historical data, and a corresponding reduction in winter peak loads.

5.1.1 Winter Climate Impacts in the CAISO Region

Figure 8 shows the distribution of space heating loads (left) and space cooling loads (right) during high-load hours in the 2045 forecast year for both the Reference Scenario (top), and the Net-Zero Scenario (bottom). “High-load” hours shown in the figure included the top 10 winter load hours for each downscaled GCM in each weather year used to represent the 2045 forecast year. The distributions show outputs from load forecasts across all four GCMs and all weather years

combined to provide a broader illustration of the resulting climate impacts on winter heating and cooling loads across the entire range of inputs. The gray bars show distributions without climate impacts, and the transparent colorful bars show distributions with climate impacts. Each bar in the distribution represents a 1 GW bin. The figure shows only the contributions greater than 1 GW, but there are also several high-load winter hours with little-to-no contributions from space heating or little-to-no contributions from space cooling.

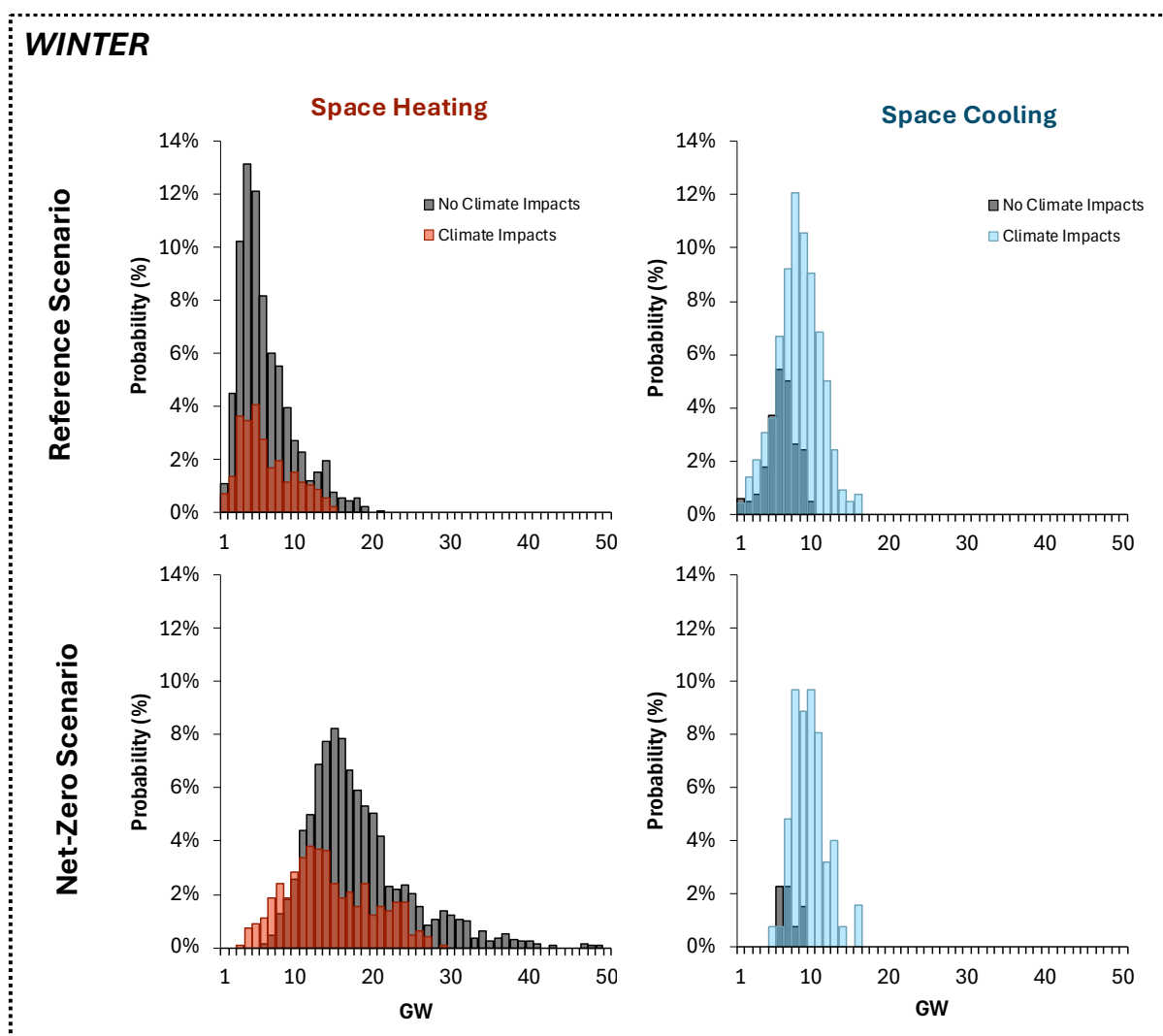


Figure 8 Distribution of winter space heating loads (left) and space cooling loads (right) in Reference Scenario (top) and Net-Zero Scenario (bottom) across the 10 highest load hours in the winter in 2045 in the CAISO region

Figure 8 reveals that in general, modeling climate impacts decreased the contribution of space heating to high-load winter hours, and increased the contribution of space cooling to high-load winter hours. The distributions further highlight the interdependence of climate impacts and electrification. The higher levels of electric space heating in the Net-Zero Scenario relative to the

Reference Scenario led to higher winter space heating electricity demands, shifting the distribution to the right in Figure 8. However, when climate impacts are layered on, fewer high-load hours in the winter are driven by space heating. This is evident in the reduced probability of high space heating loads, shown by the overall shortening of the space heating load distribution, and by the distribution shifting to the left once climate impacts have been layered on. The reduction in winter space heating demands and the increase in winter space cooling demands have opposite impacts on winter peak loads. The relative magnitude of these two competing effects and the extent to which they offset each other depends on the level of electrified space heating. This is demonstrated by the differences in how climate change impacted 1-in-2 and 1-in-10 peaks for the Reference Scenario compared to the Net-Zero Scenario (see Figure 7).

5.1.2 Summer Climate Impacts in the CAISO Region

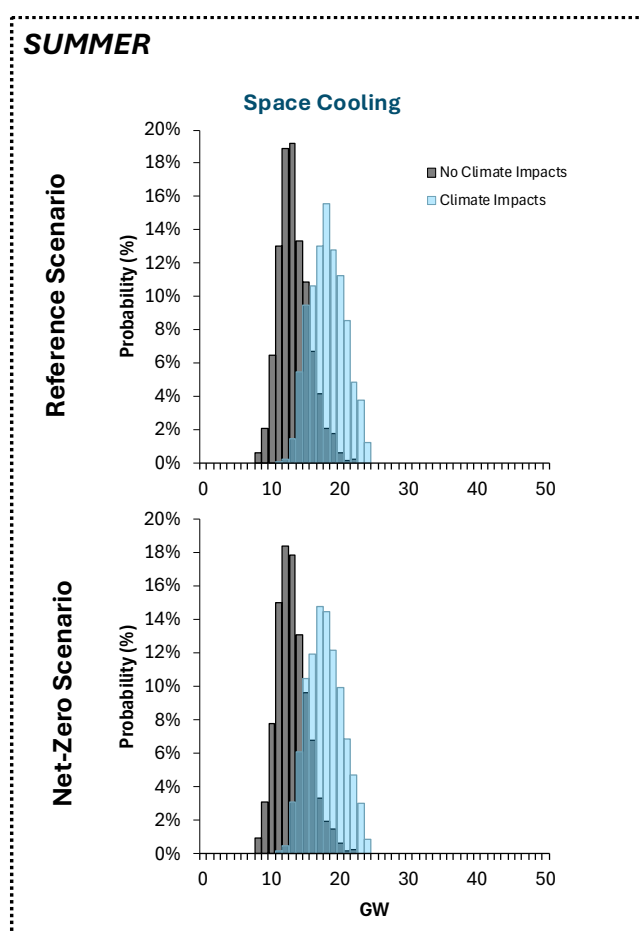


Figure 9 Distribution of summer space cooling loads in the Reference Scenario (top) and Net-Zero Scenario (bottom) across the 10 highest load hours in the summer in 2045 in the CAISO region

Figure 9 shows the space cooling load distributions across the “high-load” summer hours (analogous to the cooling load distributions shown in Figure 8 for winter). “High-load” hours shown

in the figure included the top 10 summer load hours for each downscaled GCM in each weather year for the 2045 forecast year. The distributions show outputs from load forecasts across all four GCMs and all weather years combined to provide a broader illustration of the resulting climate impacts on summer cooling loads across the entire range of inputs.³⁹ All of the high-load summer hours had contributions from space cooling that were greater than 1 GW, regardless of climate impacts. Intuitively, the climate impacts increased the cooling loads in high-load summer hours, shifting the distributions to the right for both policy scenarios.

5.1.3 *Climate Impacts Relative to Other Load Growth Drivers in the CAISO Region*

Although modeled climate impacts are one factor that can impact peak loads, climate impacts will also need to be considered alongside other drivers of load growth. For example, data center-driven load growth, policy goals that drive electrification (e.g. towards net-zero GHG emissions), and load growth consistent with other current trends are all expected to impact future peak loads in California. Figure 10 shows how climate impacts compare to other factors (i.e. load growth expected based on current trends and net zero policy goals) contributing to seasonal peak load growth by 2045 in the Net-Zero Scenario relative to 2025 in the Reference Scenario.⁴⁰ The data underlying the figure represents the median peak hour in each season across all four downscaled GCMs combined and across all weather years to provide a general picture of factors contributing to peak load growth through 2045. Climate impacts accounted for approximately 22% of the relative summer peak load growth (approximately 8 GW), with current trends and policy goals accounting for the other 78%.

³⁹ This is analogous to Figure 8 that was shown for the winter season. However, space heating is not shown given that it has little-to-no contribution to high-load summer hours.

⁴⁰ “Current trends” shown in Figure 10 represent load growth between 2025 and 2045 in the Reference Scenario without climate impacts modeled. A detailed description of scenario assumptions is provided in Appendix A.1.

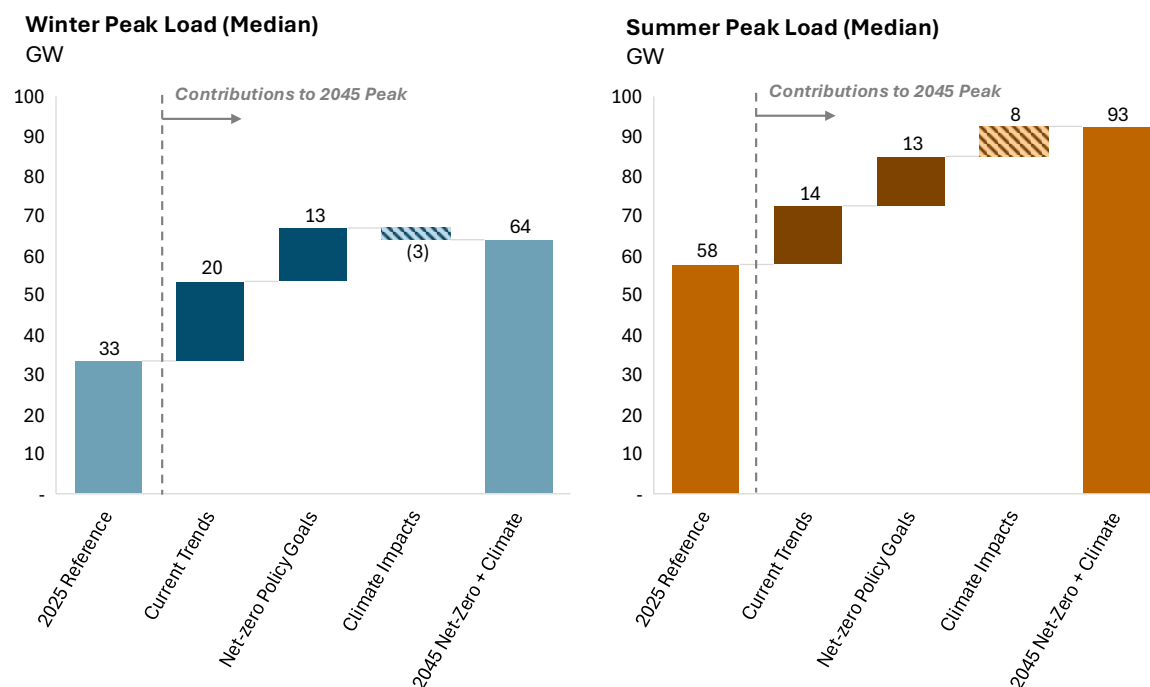


Figure 10 Contributions of key drivers to median peak load growth from 2025-2045 for the CAISO region

As demonstrated by Figure 10, there are many factors that may contribute to significant load growth by 2045. For simplicity of visualization, Figure 10 shows single deterministic values for the median peak across GCMs and weather years, but in reality, each contributor to load growth also carries its own uncertainty that leads to a range of plausible outcomes rather than a single value. The present study captured a range of outcomes for climate impacts, but did not focus on uncertainties across other dimensions. The climate-informed load forecasts included a range of climate models and weather years that contributed to a range of peak loads, as demonstrated by the variation shown across GCMs and across weather years shown in Figure 7. However, the range of plausible outcomes driven by uncertainty in future climate may in fact be much broader, especially given that the current study only considered one climate scenario to evaluate future climate impacts (SSP3-7.0).

Figure 10 illustrates that electricity demand growth from current trends (including population and data center-related load growth) as well as from net-zero policy goals (driving electrification) is likely to be much larger than the peak demand impacts associated with future climate impacts. Future climate impacts, particularly hotter summer temperatures, can be alleviated by investments in high efficiency building shells, passive cooling solutions, and high efficiency air conditioning. Warming trends in the winter due to climate impacts mean that building electrification is likely to result in lower winter peak demands than would have occurred in the absence of climate change. However, as illustrated in Figure 10, the overall trend, relative to today, will likely be a need for higher grid capacity in both the summer and the winter, regardless of climate impacts. While Figure 10 offers insight into the potential magnitude of future seasonal peak loads and the factors contributing to future changes, it should be noted that the timing of seasonal peak loads (i.e. the hour of day in which

the peak occurs) is dependent on the full combination of end-uses across sectors (e.g. transportation load, building load, etc.). Both the timing of peak loads and the coincident availability of electricity generation resources will contribute to critical periods in the future that may drive electricity sector resource needs. This will be explored further in the downstream electric sector analysis and final report for this project.

5.2 Climate Impacts on Peak Loads Across Other WECC Regions

Climate-informed load forecasts were also developed for other regions across the WECC outside of California. Modeled regions included the following groups of states:

- + WECC_NW: Washington, Oregon, Idaho
- + WECC_SW: Nevada, Arizona, New Mexico
- + WECC_MTN: Colorado, Utah, Wyoming, Montana

Figure 11 shows a comparison of the 1-in-2 and 1-in-10 peak loads with and without climate impacts under the Net-Zero Scenario across all regions modeled across the WECC for the 2045 forecast year. The data shown reflects aggregate statistics across all four GCMs for each region. 2025 Reference Scenario peak loads are also shown for comparison. The climate impacts on peak loads were most pronounced in the CAISO region relative to other regions modeled. The CAISO region, WECC_SW region, and WECC_MTN region all remain summer-peaking and exhibit increased summer peak loads due to increased demand for air conditioning. The WECC_NW region remains winter peaking, with climate impacts reducing the peak due to warmer winters.

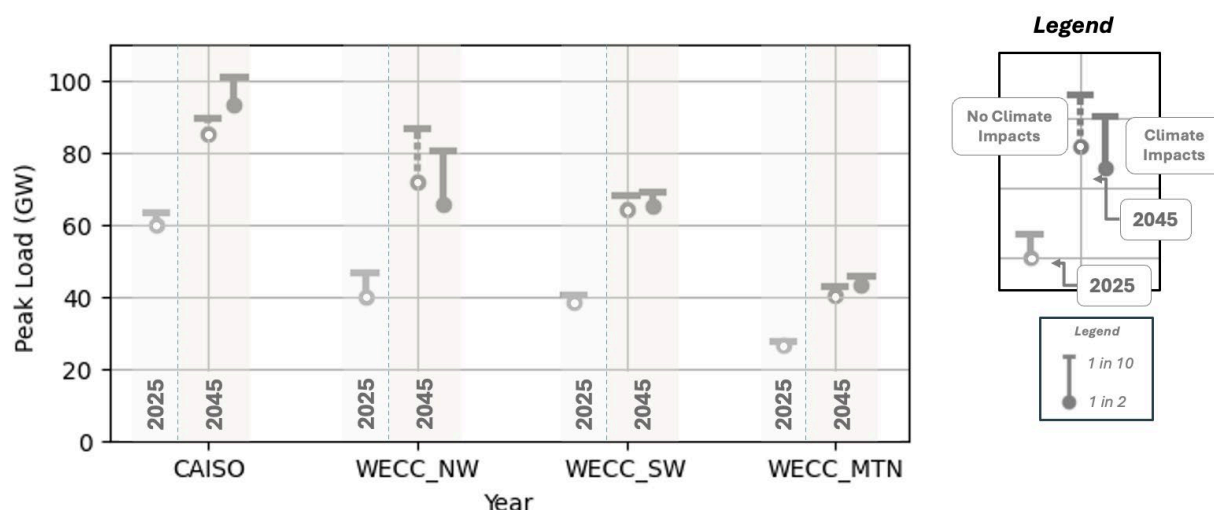


Figure 11 Climate impacts on peak loads for each modeled region for the Net-Zero Scenario across all GCMs in 2045

6 Conclusions and Lessons Learned

Through the process of developing the climate-informed load forecasts for the current study, the project team identified key takeaways to consider in future studies:

- + **Modeling of future climate impacts to electric load growth and peak demand suggests that California is likely to remain summer peaking.** Even in scenarios with high levels of building electrification for space heating, climate informed load forecasting suggests that California is likely to remain a summer peaking region, due to high air conditioning loads and relatively mild winter heating loads. Winter warming may lead to an aggregate shift in winter months from space heating (with heat pumps) to space cooling, as well as reduced peak day heating demands.
- + **Climate change is likely to accelerate electricity peak demand growth.** This study showed substantial load growth from the present through 2045 across a range of key drivers including population growth, electrification towards net-zero greenhouse gas emission goals, and climate impacts. Climate impacts accounted for approximately 22% of the summer peak load growth across drivers in the CAISO region in the Net-Zero Scenario. These impacts could be alleviated, in part, by investments in energy efficient building designs and high efficiency cooling equipment beyond what is modeled in this study.

The project team also identified several lessons learned that may be considered for future work incorporating climate impacts into grid planning, and for climate-informed load forecasting in particular:

- + **Continued development of climate model outputs at the hourly time scale may aid in downstream modeling efforts.** Many of the standard modeling tools and processes that are

used for load forecasting require hourly input data. While it is possible to post-process climate signals on the daily or monthly timeframe for use in hourly modeling (e.g. hourly load forecasting), doing so introduces additional complexity into the modeling process and may not be practical in an applied, or regulatory setting. The availability of hourly climate data allowed for more seamless integration into load forecasting models used in this study. Having data available at this granularity also eased the burden of coordination needed between the load forecasting project team and collaborating climate scientists in this study by limiting the need for post-processing steps that would have required additional in-depth understanding of the underlying climate science. This may also be beneficial in future studies conducted by electricity system planners, given that not all project teams have access to climate scientists to guide their post-processing decisions which are crucial in making sure that the climate impacts are being correctly represented by downstream models.

- + **Caution must be exercised in selecting climate datasets.** When working with simulated climate data, our team found that careful attention was required to ensure alignment across datasets being used for model inputs. For example, in the input data setup, the team initially tried to benchmark future GCM-derived temperature data against ERA5 reanalysis data⁴¹ to extrapolate a changes caused by climate impacts. However, the underlying differences between reanalysis data and downscaled GCM data created misalignment in the temperature trends resulting in an unclear signal when comparing historical and future conditions. After further consultation with climate scientists, the direct GCM-derived data for historical years was used instead of the ERA5 data, which improved the signal alignment between historical years and future years.
- + **Utilizing end-use specific models for forecasting climate impacts on load may provide greater explainability.** This study leveraged end-use specific models that allowed the project team to analyze the climate impacts on relevant end-uses (e.g. space heating and space cooling) in isolation. This allowed for a greater level of explainability and understanding of the drivers of resulting changes in peak loads. End-use specific models (e.g. separate models and approaches for vehicle electrification, electrified heating, space cooling, etc.) are a common feature of state-of-the-art load forecasting approaches. When extending existing load forecasting techniques to future climate, the ability to isolate the impacts of climate on specific end-uses is crucial for explaining the directionality of climate impacts in a region. Despite the additional modeling burden that the climate data represents, we recommend maintaining model fidelity across end-uses in order to explain and understand the impacts of that future weather data on hourly load shapes for the purposes of grid modeling.
- + **Expanding coverage of potential climate impacts requires prudent consideration of data processing limitations.** This study found clear directional impacts from climate on peak loads. The magnitude of this impact varied based on which climate model was selected, and what range of weather years was selected to represent future conditions. Expanding the modeling to include even more weather realizations would further illuminate the full picture of uncertainty. However, expanding modeling to include additional data beyond what was considered in this

⁴¹ ERA5 data refers to the ECMWF reanalysis data V5 at a 0.25 degree latitude/longitude grid.

study would have required additional resources for data processing that are beyond the standard requirements for load forecasting efforts, which typically only consider up to 30 weather years of historical data (and sometimes less). In this study, even with a relatively small subset of just four downscaled GCMs, there were hundreds of weather years to evaluate, an order of magnitude increase in the amount of data to ingest relative to typical load forecasting efforts. While broadening the range of climate conditions processed for grid-related analysis will yield a more complete picture of plausible outcomes, it comes at a cost: large datasets will increase model runtimes, and hours spent analyzing results. There is a clear tradeoff between expanding the input dataset considered and project timeline and complexity that must be balanced depending on the use case. Taking this study as an upper limit for constrained project teams, there are a few alternative approaches that future project teams could take:

- Emphasize explicit modeling of conditions of interest (e.g. extreme weather scenarios). Pre-selecting downscaled climate datasets for the region of interest based on book-end scenarios (e.g. select datasets from a particularly hot model to capture extreme effects on climate in a summer-peaking region) may aid in limiting the amount of climate data to be ingested, while still preserving the robustness of the scenario analysis and addressing the uncertainty in future climate change.
- Select a subset of years to model based on desired criteria; pick representative samples based on clustering of the data, or pick a random sample. This would enable more weather models to be included without increasing the total dataset size. Results from the next phases of this study will inform what to prioritize in this selection process with regards to downstream impacts on electric sector planning.

The project team plans to continue building on the progress and learnings demonstrated in this interim report. The climate-informed load forecasts described in this study will serve as key inputs to the forthcoming electricity system analysis, which will develop optimized resource portfolios across the Western Electricity Coordinating Council (WECC) region, considering both scenario-based and stochastic perspectives. The forthcoming electricity system portfolios will offer insights for consideration for regionalized grid planning in a future impacted by climate change.

Appendix A. PATHWAYS Inputs & Assumptions

This appendix describes the inputs and assumptions used to generate annual loads using E3's PATHWAYS model.

A.1. Policy Scenario Assumptions

Policy assumptions for each scenario determined how much electric load growth occurs from the base year through 2050. Two different policy scenarios were modeled for California regions, a **Reference** scenario and a **Net Zero** scenario. For California, the Reference scenario included current policy measures and trends. The Net Zero scenario added policy measures, incremental to the Reference, that align with the 2022 CARB Scoping Plan Update to achieve Net Zero emissions by 2045.⁴² Policy scenario assumptions for California are summarized in Table 5.

Table 5 California PATHWAYS Policy Scenario Assumptions

Sector	Reference Scenario	Net Zero Scenario <i>(Incremental measures relative to reference scenario)</i>
Buildings	+ Title 20⁴³: Screw-base CFL bulbs will be phased out by 2024, pin-base CFL and fluorescent tubes by 2025 + Title 24⁴⁴: 100% new construction electric water heating and space heating starting in 2026 + BAAQMD Zero-NOx standards⁴⁵: 100% replacement on burnout for BAAQMD by: 2027 for water heating; 2029 for space heating + SCAQMD Zero-NOx standards⁴⁶: 100% replacement on burnout for water heating by 2029 + Historical trends for heat pump space heating adoption by state + Heat pump water heater “Low” scenario from EPA analysis	+ New construction: all electric appliances beginning in: 2026 (residential); 2027 (commercial) + Existing residential buildings: 80% of appliance sales are electric by 2030 and 100% by 2035 + Existing commercial buildings: 80% of appliance sales are electric by 2030 and 100% by 2045 + Heat pump target: 6 million heat pumps installed statewide by 2030 + All-electric homes target: 3 million all-electric homes by 2030 and 7 million by 2035 + Energy efficiency: Aligned with national device standards and energy efficiency trends over time

⁴² <https://ww2.arb.ca.gov/our-work/programs/ab-32-climate-change-scoping-plan/2022-scoping-plan-documents>

⁴³ <https://www.energy.ca.gov/publications/2021/california-code-regulations-title-20-public-utilities-and-energy-division-2>

⁴⁴ <https://www.dgs.ca.gov/bsc/codes>

⁴⁵ <https://www.baaqmd.gov/rules-and-compliance/rule-development/building-appliances>

⁴⁶ <https://www.aqmd.gov/home/rules-compliance/rules/scaqmd-rule-book/proposed-rules/rule-1146-2>

	+ Energy efficiency: Aligned with national device standards and energy efficiency trends over time	
Transportation	+ Advanced Clean Cars II (ACC II)⁴⁷ + Vehicle miles traveled (VMT) per capita reduced for light-duty vehicles 4% below 2019 levels by 2045, aligned with Mobile Source Strategy (MSS) BAU scenario⁴⁸ + Advanced Clean Trucks (ACT)⁴⁹ + Advanced Clean Fleets (ACF)⁵⁰	+ 100% of medium- and heavy-duty vehicle sales are zero-emissions vehicles (ZEVs) by 2040 + SB375⁵¹: VMT per capita for light-duty vehicles reduced 25% below 2019 levels by 2030 and 30% below 2019 levels by 2045 + Aviation: AB197⁵²: 20% of aviation fuel demand is met by electricity (batteries) or hydrogen (fuel cells) in 2045. Sustainable aviation fuel meets the rest of aviation demand that has not already transitioned to hydrogen or batteries + Ocean-going vessels (OGVs): 2020 OGV At-Berth regulation fully implemented, with most OGVs utilizing shore power by 2027. 25% of OGVs utilize hydrogen fuel cell electric technology by 2045 + Rail: 100% of passenger and other locomotive sales are ZEV by 2030. 100% of line haul locomotive sales are ZEV by 2035. Line haul and passenger rail rely primarily on hydrogen fuel cell technology, and others primarily use electricity
Industry	+ Aligned with current trends⁵³	+ Agriculture and construction: 25% of energy demand electrified by 2030 and 75% by 2045 + Food Production: 7.5% of energy demand electrified by 2030 and 75% by 2045 + Chemical and paper: electrify 0% of boilers by 2030 and 100% by 2045.

⁴⁷ <https://ww2.arb.ca.gov/our-work/programs/advanced-clean-cars-program/advanced-clean-cars-ii>

⁴⁸ <https://ww2.arb.ca.gov/resources/documents/2020-mobile-source-strategy#:~:text=The%20actions%20contained%20in%20the,growth%20in%20the%20mobile%20sector.>

⁴⁹ <https://ww2.arb.ca.gov/our-work/programs/advanced-clean-trucks>

⁵⁰ <https://ww2.arb.ca.gov/our-work/programs/advanced-clean-fleets#:~:text=The%20ACF%20Regulation%20requires%20fleets,in%20the%202036%20model%20year.>

⁵¹ <https://ww2.arb.ca.gov/our-work/programs/sustainable-communities-program/sb-375-regional-targets>

⁵² <https://ww2.arb.ca.gov/sites/default/files/2022-11/2022-sp-appendix-c-ab-197-measure-analysis.pdf>

⁵³ <https://www.eia.gov/outlooks/archive/aeo23/>

		Hydrogen for 25% of process heat by 2035 and 100% by 2045. Electrify 100% of other energy demand by 2045 + Petroleum refining energy demand ramped down in line with in-state petroleum demand. CCS on majority of operations by 2030, beginning in 2028 + Oil & gas extraction ramped down to 30% below 2019 levels by 2030 and 40% by 2045 + Stone, Glass, and Cement: CCS on 40% of operations by 2035 and all facilities by 2045 + Other Industry: 0% of energy demand electrified by 2030 and 50% by 2045
Data centers	+ E3 internal forecast on data center growth over time (loads assume 79% annual capacity factors based on CEC analysis of data centers within the Silicon Valley Power service territory)	+ E3 internal forecast on data center growth over time (loads assume 79% annual capacity factors based on CEC analysis of data centers within the Silicon Valley Power service territory)

Each state in the Western U.S. was also modeled. Two scenarios were modeled for states outside of California, a **Reference** scenario and a **High Climate Action** scenario. In the Reference scenario, the other states have their own Reference inputs based on current policies and trends. In the High Climate Action scenario, states that have enacted their own Net Zero policies have a set of incremental measures, while the remaining states are modeled with the Reference inputs. Policy scenario assumptions for other states are summarized in Table 6.

Table 6 Non-California PATHWAYS Policy Scenario Assumptions

Sector	Reference Assumptions	Net Zero Assumptions <i>(Applies only to states with net zero policies in the “High Climate Action” scenario)</i>
Buildings	+ Historical trends for heat pump space heating adoption by state + Heat pump water heater “Low” scenario from EPA analysis	+ Heat pump sales increase to 100% for space and water heating by 2040
Transportation	+ Historical trends by state, no Biden-era EPA emissions standards	+ Biden-era EPA emissions standards

	+ ACC II and ACT in states that have adopted them	
Industry	+ No manufacturing electrification + Announced semiconductor plan investment by state + Existing electrolysis loads	+ Electrification from the “Collective Action” scenario from the US Climate Alliance “All Hands on Deck” report⁵⁴ + Additional loads due to projected clean energy manufacturing + Electrolysis consistent with Biden Administration Long-term Strategy hydrogen demands
Data centers	+ E3 forecast on data center growth over time	+ E3 forecast on data center growth over time

A.2. PATHWAYS Default Input Data Sources

PATHWAYS calculates energy demand for the building and transportation sectors by taking the base year energy demand and applying a stock rollover model to calculate future energy demands. The stock rollover is based on key drivers which determine the overall growth in energy demand, policy measures defined in each scenario, and the lifetime of devices (e.g. vehicles, appliances) that serve end-uses in each sector. Inputs used for the base year and stock rollover are summarized in Table 7.

Table 7 PATHWAYS Input Data Sources

Input	Data Source
Key drivers (population, number of housing units, commercial square footage, and growth rates)	California Energy Demand Forecast 2023, 2023-2040 Baseline Forecast Planning Area Economic and Demographic Assumptions (Form 2.2) ⁵⁵
Base year electricity and natural gas sectoral energy demands	2023 Integrated Energy Policy Report (IEPR) ⁵⁶
Base year sectoral energy demands for fuels other than electricity and natural gas	U.S. Energy Information Administration (EIA) State Energy Data System (SEDS) ⁵⁷
Device Lifetimes, Transportation	EPA MOVES 3 ⁵⁸
Device Lifetimes, Buildings	EIA Residential Energy Consumption Survey (RECS) 2020 ⁵⁹ , LEAP Weibull Curves

⁵⁴ <https://usclimatealliance.org/report/2023-annual-report/>

⁵⁵ [2023-iepr-workshops-notice-and-2](https://www.eia.gov/state/seds/seds-data-complete.php?sid=US)

⁵⁶ [2023-iepr-workshops-notice-and-2](https://www.eia.gov/state/seds/seds-data-complete.php?sid=US)

⁵⁷ <https://www.eia.gov/state/seds/seds-data-complete.php?sid=US>

⁵⁸ <https://www.epa.gov/moves/tools-develop-or-convert-moves-inputs>

⁵⁹ <https://www.eia.gov/consumption/residential/data/2020/>

The building (residential and commercial) and transportation sectors are further divided into subsectors representing distinct end-uses (e.g. space heating, cooking, etc.). Each subsector utilizes inputs for a range of different devices available to serve the end-use (e.g. devices for space heating include heat pumps, electric resistance heat, gas furnace, etc.). PATHWAYS uses the stock (number of devices), service demand (energy output required), and device efficiency to calculate the energy demand of each subsector. Default data sources for each subsector are summarized in Table 8.

Table 8 PATHWAYS Default Device Input Data Sources

Subsector	Stocks	Service Demands	Device Efficiency
Residential Central Air Conditioning	EIA RECS 2020 ⁶⁰	EIA NEMS ⁶¹	EIA NEMS
Residential Clothes Drying	EIA RECS 2020	EIA NEMS	EIA NEMS
Residential Clothes Washing	EIA RECS 2020	EPA Energy Star data ⁶²	EIA NEMS
Residential Cooking	EIA RECS 2020	EIA NEMS	ACEEE Induction Cooking Technology Design and Assessment, 2014 ⁶³
Residential Dishwashing	EIA RECS 2020	EIA NEMS	EIA NEMS
Residential Freezing	EIA RECS 2020	EIA NEMS	EIA NEMS
Residential Exterior Lighting	DOE 2020 ⁶⁴	EIA NEMS	EIA NEMS
Residential General Service Lighting	DOE 2020	EIA NEMS	EIA NEMS
Residential Linear Fluorescent Lighting	DOE 2020	EIA NEMS	EIA NEMS
Residential Reflector Lighting	DOE 2020	EIA NEMS	EIA NEMS
Residential Refrigeration	EIA RECS 2020	EIA NEMS	EIA NEMS
Residential Room Air Conditioning	EIA RECS 2020	EIA NEMS	EIA NEMS
Residential Single Family Space Heating	EIA RECS 2020	EIA NEMS	EIA NEMS
Residential Multi Family Space Heating	EIA RECS 2020	EIA NEMS	EIA NEMS
Residential Water Heating	EIA RECS 2020	EIA NEMS	EIA NEMS

⁶⁰ U.S. Department of Energy, Energy Information Administration. (2023). *Residential Energy Consumption Survey*; <https://www.eia.gov/consumption/residential/data/2020/>

⁶¹ U.S. Department of Energy, Energy Information Administration. (2023). *National Energy Modeling System*; <https://www.eia.gov/outlooks/aeo/nems/documentation/>

⁶² <https://www.ecfr.gov/current/title-10/chapter-II/subchapter-D/part-430/subpart-B/appendix-Appendix%20J2%20to%20Subpart%20B%20of%20Part%20430>

⁶³ <https://www.aceee.org/files/proceedings/2014/data/papers/9-702.pdf>

⁶⁴ U.S. Department of Energy, Office of Energy Efficiency & Renewable Energy. (2020). *Adoption of Light-Emitting Diodes in Common Lighting Applications*; <https://www.energy.gov/sites/default/files/2020/09/f78/ssl-led-adoption-aug2020.pdf>

Commercial Air Conditioning	EIA CBECS 2018 ⁶⁵	EIA NEMS	EIA NEMS
Commercial Cooking	EIA CBECS 2018	EIA NEMS	EIA NEMS
Commercial General Service Lighting	DOE 2020	EIA NEMS	EIA NEMS
Commercial HID Lighting	DOE 2020	EIA NEMS	EIA NEMS
Commercial Linear Fluorescent Lighting	DOE 2020	EIA NEMS	EIA NEMS
Commercial Refrigeration	EIA CBECS 2018	EIA NEMS	EIA NEMS
Commercial Ventilation	EIA CBECS 2018	EIA NEMS	EIA NEMS
Commercial Space Heating	EIA CBECS 2018	EIA NEMS	EIA NEMS
Commercial Water Heating	EIA CBECS 2018	EIA NEMS	EIA NEMS
Transportation Light Duty Cars	FHWA 2021 ⁶⁶	FHWA 2021	NHTSA ⁶⁷
Transportation Light Duty Trucks	FHWA 2021	FHWA 2021	NHTSA
Transportation Light Medium Duty Trucks	2021 VIUS ⁶⁸	2021 VIUS	EIA AEO 2023 ⁶⁹
Transportation Medium Duty Trucks	2021 VIUS	2021 VIUS	EIA AEO 2023
Transportation Heavy Duty Trucks (Short-haul)	2021 VIUS	2021 VIUS	EIA AEO 2023
Transportation Heavy Duty Trucks (Long-haul)	2021 VIUS	2021 VIUS	EIA AEO 2023
Transportation Buses	FHWA 2021	FHWA 2021	ANL 2021 ⁷⁰

A.3. Base Year Benchmarking

The process of calibrating PATHWAYS model inputs so that base year energy demand outputs align with historical data is referred to as benchmarking. Base year model outputs were benchmarked to the CEC 2023 Integrated Energy Policy Report (IEPR) demand forecast⁷¹ at the planning area level for electricity and natural gas, and historical energy consumption from the EIA State Energy Data System

⁶⁵ U.S. Department of Energy, Energy Information Administration. (2022). *Commercial Building Energy Consumption Survey*; <https://www.eia.gov/consumption/commercial/data/2018/>

⁶⁶ U.S. Department of Transportation, Federal Highway Administration. (2022). *Highway Statistics 2021*; <https://www.fhwa.dot.gov/policyinformation/statistics/2021/>

⁶⁷ <https://www.nhtsa.gov/file-downloads?p=nhtsa/downloads/CAFE/2022-FR-LD-2024-2026/Central%20Analysis/>

⁶⁸ U.S. Census Bureau. (2023). *2021 Vehicle Inventory and Use Survey*; <https://www.census.gov/programs-surveys/vius.html>

⁶⁹ U.S. Department of Energy, Energy Information Administration. (2023). *Annual Energy Outlook 2023*; <https://www.eia.gov/outlooks/aeo/>

⁷⁰ U.S. Department of Energy, Argonne National Laboratory. (2023). *Vehicle Technologies and Hydrogen and Fuel Cell Technologies Research and Development Benefits Analysis*; <https://vms.taps.anl.gov/reports/u-s-doe-vto-hfto-r-d-benefits-analysis-mdhd/>

⁷¹ <https://www.energy.ca.gov/data-reports/reports/2023-integrated-energy-policy-report/2023-iepr-workshops-notices-and-2>

(SEDS)⁷² at the state level. For this study, 2022 was used as the base year given that at the time of analysis, 2022 was the most recent year in the CARB inventory. Details on the benchmarking process for the California PATHWAYS model are provided in Table 9. For other Western U.S. states, benchmarking was conducted at the state level using EIA SEDS.

Table 9 California 2022 Base Year Benchmarking Assumptions

Sector	Benchmarked to	Benchmarking Adjustments Made
Buildings (Residential)	+ Electricity and Natural Gas: CEC 2023 IEPR + Other Fuels: EIA SEDS	+ Aligned stocks (per capita) and stock share by fuel/technology with the CEC 2019 Residential Appliance Saturation Survey (RASS)⁷³ + Service demands for space heating, water heating, and refrigeration aligned with RASS
Buildings (Commercial)	+ Electricity and Natural Gas: CEC 2023 IEPR + Other Fuels: EIA SEDS	+ Space heating and water heating service demands scaled so that statewide commercial natural gas consumption in PATHWAYS matches IEPR in the base year
Transportation	+ Electricity: CEC 2023 IEPR + Other Fuels: EIA SEDS	+ Base Year efficiency (MPG) calculated from CARB EMFAC 2021 Inventory⁷⁴ + Light-Duty Vehicle (LDV) stocks (per capita) and stock share by fuel aligned with CEC vehicle registration data⁷⁵ + Adjusted share of residual fuel oil and distillate in the shipping sector based on International Renewable Energy Agency (IRENA) data⁷⁶ + Adjusted Heavy Duty Vehicle (HDV) vehicle miles travelled (VMT) to match EIA SEDS distillate demand

⁷² <https://www.eia.gov/state/seds/seds-data-complete.php?sid=US>

⁷³ <https://www.energy.ca.gov/sites/default/files/2021-08/CEC-200-2021-005-ES.pdf>

⁷⁴ <https://ww2.arb.ca.gov/our-work/programs/msei/on-road-emfac>

⁷⁵ "Vehicle_Population_Last_updated_04-30-2024_ada.xlsx", from <https://www.energy.ca.gov/files/zev-and-infrastructure-stats-data>

⁷⁶ https://www.irena.org/-/media/Files/IRENA/Agency/Publication/2021/Oct/IRENA_Decarbonising_Shipping_2021.pdf

Industry	+ Electricity: CEC 2023 IEPR + Other fuels: EIA SEDS	+ Fuel consumption allocated to regions and subsectors based on proportions in the CARB 2022 Emissions Inventory⁷⁷ + Industrial energy demand in the PATHWAYS model is a direct input from IEPR and SEDS; no further benchmarking is needed to match total demand
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⁷⁷ <https://ww2.arb.ca.gov/ghg-inventory-data>