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Key Points:

- We identify a decarbonization pathway for the power system that is robust to future climate realizations
- Our framework is extensible to long-term planning by utilities, regions, and regulators
- Large climate ensembles expose significant resource adequacy vulnerabilities in alternative decarbonization pathways

Supporting Information:

Supporting Information may be found in the online version of this article.

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Identifying Robust Decarbonization Pathways for the Western U.S. Electric Power System Under Deep Climate Uncertainty

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Abstract Climate change threatens the resource adequacy of future power systems. Existing research and practice lack frameworks for identifying decarbonization pathways that are robust to climate-related uncertainty. We create such an analytical framework, then use it to assess the robustness of alternative pathways to achieving 60% emissions reductions from 2022 levels by 2040 for the Western U.S. power system. Our framework integrates power system planning and resource adequacy models with 100 climate realizations from a large climate ensemble. Climate realizations drive electricity demand; thermal plant availability; and wind, solar, and hydropower generation. Among five initial decarbonization pathways, all exhibit modest to significant resource adequacy failures under climate realizations in 2040, but certain pathways experience significantly less resource adequacy failures at little additional cost relative to other pathways. By identifying and planning for an extreme climate realization that drives the largest resource adequacy failures across our pathways, we produce a new decarbonization pathway that has no resource adequacy failures under any climate realizations. This new pathway is roughly 5% more expensive than other pathways due to greater capacity investment, and shifts investment from wind to solar and natural gas generators. Our analysis suggests modest increases in investment costs can add significant robustness against climate change in decarbonizing power systems. Our framework can help power system planners adapt to climate change by stress testing future plans to potential climate realizations, and offers a unique bridge between energy system and climate modeling.

Plain Language Summary Over the past few years, large power outage events in California and Texas have underscored the vulnerability of our power systems to extreme weather. By increasing the intensity and frequency of extreme weather, climate change could lead to more power outages. In response, power system planners are grappling with how to plan for extreme weather and climate change when making investment decisions, such as in wind and solar power. In our research, we build and apply a new analytical framework for making power system investment decisions under climate change. Our framework draws on a hundred realizations of future climate, and integrates weather in those realizations with power system models that make investment decisions and explore the risk of power outages. We find five alternative investment pathways all could suffer from moderate to significant power outages under possible climate realizations by 2040. But by identifying what realizations drive outage risk in these pathways, we construct a new pathway that does not exhibit outage risks to our future climate realizations. Overall, these insights demonstrate the value of our new analytical framework for making better investment decisions under uncertainty posed by climate change.

1. Introduction

Rapidly transitioning to a decarbonized electric power sector is crucial to aggressively mitigate climate change and meet emissions reductions targets (Clarke et al., 2022; Rogelj et al., 2015). In the United States, the Inflation Reduction Act (IRA) is poised to accelerate low-carbon investments in the power sector, which could approach 370 billion USD by 2033 (Jenkins et al., 2022; Pacala et al., 2021). Which power sector decarbonization pathway will be taken remains uncertain, where a pathway is defined by where, when, and what decarbonization investments occur (Berrill et al., 2022; Cole et al., 2021; Davis et al., 2018; Denholm et al., 2022; Jenkins et al., 2021; Ralston Fonseca et al., 2021a, 2021b; Wessel et al., 2022). As they decarbonize, bulk (or

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transmission-scale) power systems will be increasingly affected by climate change (Lee et al., 2023). Increasing ambient air temperatures will increase peak and total electricity demand (Auffhammer et al., 2017; Craig, Cohen, et al., 2018; Ralston Fonseca et al., 2019) and reduce available capacity from thermal and solar generators (Bartos & Chester, 2015; Craig, Cohen, et al., 2018; Henry & Pratson, 2016; Miara et al., 2017). Wind, solar, and precipitation changes will also affect wind, solar, and hydropower generation potential (Craig, Cohen, et al., 2018; Karnauskas et al., 2018; Schewe et al., 2014; Turner et al., 2017). These effects could compound to undermine resource adequacy (RA), or a system's ability to continually balance electricity supply and demand (Ralston Fonseca et al., 2021a, 2021b; Sundar et al., 2023; Turner et al., 2019). Understanding the vulnerability of decarbonizing power systems to potential future climate realizations is critical for achieving reliable, affordable, and clean power systems—the focus of our study (Craig et al., 2022; Wessel et al., 2022).

To account for decarbonization- and climate-related uncertainty in investment decisions, prior literature optimizes capacity investment decisions given different decarbonization pathways and future climate scenarios (Abdin et al., 2019; Bloomfield et al., 2021; Kozarcanin et al., 2019; Ralston Fonseca et al., 2021a; Ralston Fonseca et al., 2021b; Santos da Silva et al., 2021; Schlott et al., 2018; Simoes et al., 2021; Webster et al., 2022; Wessel et al., 2022). This literature uses sensitivity or scenario analysis to incorporate climate-related uncertainty within deterministic modeling frameworks. For instance, Fonseca et al. (Ralston Fonseca et al., 2021a, 2021b) sample three of 20 global climate models (GCMs) to include as scenarios in a deterministic long-term power system planning model. In other words, this literature aims to improve investment decisions by improving predictions of future weather within standard modeling frameworks—a “predict-then-act” approach to climate adaptation. But climate change poses deep uncertainty (Weaver et al., 2013), which undermines the value of “predict-then-act” approaches (Marchau et al., 2019), particularly for power system planning models that must significantly simplify uncertainty to remain computationally tractable. Deep uncertainty is characterized by uncertainty in how a system works and its boundaries, which leads to significant uncertainty in the probability distributions of scenarios and consequences (Marchau et al., 2019). In the context of climate change, deep uncertainty arises from disagreement around which future CO_2 emissions pathway the globe will follow (i.e., emissions scenario uncertainty); global climatic changes resulting from those pathways (i.e., climate sensitivity and structural uncertainty); and local meteorological changes resulting from global climatic changes (i.e., parametric uncertainty) (Fourth National Climate Assessment, 2018; Hallegatte et al., 2012; WG, 2013). In the near-term (prior to 2050), inter-annual (or internal) climate variability, which is driven by the dynamics of the climate system and sensitive to initial conditions (Deser et al., 2012; Hawkins & Sutton, 2009; Lehner & Deser, 2023; Lehner et al., 2020), is the primary source of climate-related uncertainty (Lehner et al., 2020; Schwarzwald & Lenssen, 2022). Under deep uncertainty, methods focused on identifying robust strategies or alternatives are better suited to informing decisions than “predict-then-act” methods (Marchau et al., 2019). Such decision support is urgently needed by power system planners and regulators, who are tasked with ensuring resource adequacy across a wide range of potential future climate realizations, which combine secular trends and inter-annual climate variability (Lehner & Deser, 2023). Recent rolling outages in California and Texas (CPUC, CAISO, & CEC, 2021; Mays et al., 2022) and resource adequacy warnings elsewhere in the United States (North American Electric Reliability Corporation, 2021) underscore this urgency.

In response to these needs, we construct a new analytical framework for planning decarbonizing power systems under deep climate uncertainty by drawing on a concept from the decision science literature: robust decision making (RDM) (Lempert, 2003; Marchau et al., 2019). RDM has been used to inform climate adaptation strategies, for example, in water resources management (Fischbach et al., 2017; Giuliani & Castelletti, 2016; Lempert & Groves, 2010; Markolf et al., 2019; Reis & Shortridge, 2020; Shortridge & Guikema, 2016; Smith et al., 2022). It has also been used in the power sector, for example, to evaluate policy strategies for European power systems against shocks (Nahmmacher et al., 2016). But our framework is the first to apply RDM to planning decarbonizing power systems under deep climate uncertainty. By integrating power system planning and operational models with potential climate realizations from a single model initial-condition large ensemble (SMILE) (Deser et al., 2020; Maher et al., 2021), our framework generates alternative decarbonization pathways; characterizes the vulnerability of and trade-offs between those pathways under potential climate realizations; and uses generated insights to identify new alternative decarbonization pathways that are robust to climate-related uncertainty (Figure 1). SMILEs have limited prior use in power systems research (van der Wiel, Bloomfield, et al., 2019; van der Wiel, Stoop, et al., 2019) even though they are designed to sample inter-annual variability and provide many

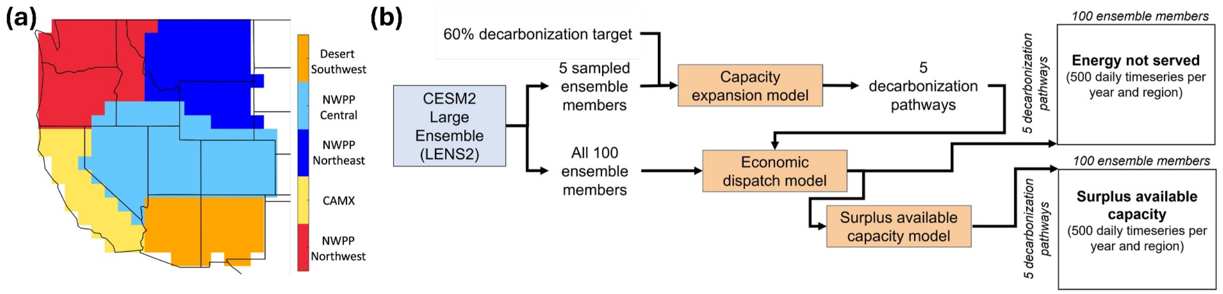

Figure 1. (a) Map of our Western Interconnect study region, which is divided into 5 sub-regions (differentiated by color). Blocks at edges of interconnect correspond to LENS2 grid cells. CAMX stands for California and Mexico and NWPP stands for Northwest Power Pool. (b) Our analytical framework integrates 100 ensemble members (or climate realizations) from the LENS2 data set with power system capacity expansion, economic dispatch, and surplus available capacity (SAC) models. For each region, this framework yields 500 annual timeseries of daily energy not served and surplus available capacity in 2040, or 1 annual timeseries of daily values (or "daily timeseries") for each climate realization, decarbonization pathway, and metric. Not shown is identification of an extreme 2040 climate realization, which is then fed back into the capacity expansion model to generate a new decarbonization pathway.

realizations of future climate, encoding multiple extreme events and a range of possible meteorological projections (Bevacqua et al., 2022, 2023).

We use our framework to answer: how can we design decarbonizing power systems to be robust against deep climate uncertainty? We conduct our study for the U.S. Western Interconnect, which we divide into five sub-regions per Western Electricity Coordinating Council's resource adequacy assessments (Figure S23 in Supporting Information S1, (WECC, 2022)). We use 100 members from the Community Earth System Model 2 (CESM2) Large Ensemble (LENS2) through 2040, which was driven by the SSP3-7.0 emissions scenario and reaches 1.65°C of global warming by 2040 relative to pre-industrial (Rodgers et al., 2021). For each ensemble member, we obtain surface air temperatures, relative humidity, surface solar radiation, 10 m wind speeds, and total runoff at daily and 1° spatial resolution (approx. 100 km by 100 km) through 2040 across our study region. While this resolution is lower than what is preferred for power system modeling, higher resolution climate data sets often do not sample as large of a range of internal climate variability as LENS2, particularly in the time-span of interest to us (through 2040) and when focused on extreme events. In selecting LENS2, we also emphasize internal variability over climate response uncertainty. For each ensemble member, we translate meteorological variables to spatially explicit timeseries of electricity demand; maximum potential wind, solar, and hydropower generation; and thermal generator deratings and forced outage rates. To analyze the vulnerability and trade-offs of alternative decarbonization pathways, we generate five decarbonization pathways by running a capacity expansion (or long-term planning) model of the Western Interconnect using power system variables from five sampled ensemble members. Our decarbonization pathways reduce interconnect-wide power system CO_2 emissions by 60% from 2022 levels by 2040. For each decarbonization pathway, we approximate its regional resource adequacy in 2040 under each of the 100 ensemble members using economic dispatch and surplus available capacity models. From this large set of alternative future systems and climate realizations, we examine vulnerabilities and trade-offs of these decarbonization pathways across potential climate realizations. Finally, we identify a future climate realization that generates the largest resource adequacy failures across decarbonization pathways in 2040, then use that climate realization to generate a new decarbonization pathway robust to all 100 ensemble members.

2. Methods

2.1. Robust Decision-Making Framework

We use robust decision-making (RDM) to quantify the robustness of alternative decarbonization pathways in the Western Interconnect power system to potential future climate realizations. We first conduct exploratory modeling to generate five decarbonization pathways for the Western Interconnect using a capacity expansion (or long-term planning) model (Section 2.2). We then stress test each decarbonization pathway to all 100 LENS2 ensemble members (Section 2.4). For each pathway and ensemble member, we approximate resource adequacy by quantifying daily Surplus Available Capacity (SAC) and Energy Not Served (ENS) in 2040 (Section 2.3). Finally, we identify the climate ensemble member that drives the largest combined energy not served (ENS) across decarbonization pathways in California (our largest load region) in 2040; rerun our planning model using

Table 1
Our Analysis Represented Within the XLRM Framework

X: Future climate realizations	L: Power system decarbonization pathways (composed of where, when, what type, and how much investment in generating and transmission occurs)
R: Response of power system assets to climate change (including hydropower, thermal generators, wind power, solar power, and electricity demand); capacity expansion model; resource adequacy models	M: Daily and annual resource adequacy; Total fixed plus variable system costs; Annual system CO_2 emissions

that ensemble member; and quantify our resource adequacy metrics for that pathway against all 100 climate ensemble members.

The "XLRM" framework is a common starting point for RDM that frames the decision space available to stakeholders (Marchau et al., 2019). X indicates uncertainties outside decisionmaker control; L indicates policy levers, or near-term actions, available to decisionmakers; M indicates performance measures that can be used to compare future scenarios; and R indicates relationships between uncertainties (X) and levers (L) and how those relationships affect performance measures (M). Table 1 provides an XLRM framework for our analysis specifically and for power system adaptation to climate change analyses more generally.

2.2. Capacity Expansion Model and Decarbonization Pathways

To generate alternative decarbonization pathways, we use a capacity expansion (or long-term planning) model. We run the capacity expansion model (CEM) in 2 year increments from 2023 to 2040, capturing coincident, spatially resolved meteorology and hydrology for each year (Section 2.4). The CEM is a deterministic linear program that minimizes fixed plus variable costs by deciding investment in wind plants, solar plants, and natural gas combined cycle (NGCC) plants with or without carbon capture and sequestration (CCS), and inter-regional transmission. These investment decisions differentiate our "decarbonization pathways." The CEM also optimizes operation of existing and new generators, and optimizes inter-regional transmission flows using the simplified transport method, which constrains inter-regional transmission flows to a fixed power rating rather than modeling AC or DC power flow. The first CEM run is initialized with the existing Western U.S. generator fleet and inter-regional transmission capacity (Text S5 in Supporting Information S1). All generator capacity investment decisions occur at the LENS2 grid cell level, that is, on a 100 by 100 km grid across our study region, while transmission investments occur at inter-regional levels. We constrain thermal plant investments to grid cells that already contain large thermal units. Given the immature state of CCS technology, we allow the CEM to invest in NGCC or coal with CCS beginning in 2031. To capture ongoing retirements of coal-fired power plants, we retire coal units with average capacity factors of less than 0.3 after each CEM run (Craig, Jaramillo, & Hodge, 2018). While we recognize the important role of grid-scale storage in decarbonizing power systems, our climate data is only available at daily resolution (Section 2.4). As such, we cannot model intra-day storage.

The CEM includes numerous system- and generator-level constraints. At the system level, the CEM balances regional supply (generation plus imports minus exports) and demand each day. We do not account for interchanges with Canada and Mexico. The CEM requires derated capacity to exceed peak demand, where derated capacity accounts for wind and solar generation potential; a fixed 5% forced outage rate for wind and solar generators; temperature-dependent FORs for thermal and hydropower plants; and weather-driven deratings of combustion turbine, combined cycle, and coal-fired plants. At the generator level, wind and solar generation is limited by daily, spatially specific wind and solar capacity factors (Section 2.4); hydropower generation is constrained by subregional monthly total generation; and generation from combustion turbine, combined cycle, and coal-fired plants is limited by daily, spatially specific meteorology.

With the CEM, we generate five decarbonization pathways that each reduce interconnect-wide CO_2 emissions by 60% from 2022 levels by 2040. To create these five pathways, we use meteorological timeseries from five sampled LENS2 members. These ensemble members are sampled to capture a range of warming and relative humidity changes within the LENS2 ensemble (Table 2). Specifically, we quantify warming level based on the difference between historic (1985–2015) and mid-century (2035–2065) mean surface temperature and relative humidity (Jones et al., 2022). Warming and relative humidity levels vary from 1.5 °C to 2.75 °C and 0.1 to −1.79, respectively, across sampled ensemble members (Figure S12 in Supporting Information S1). We present results

Table 2
Difference in Temperature (T) and Relative Humidity (RH) Between Mid-Century (2035–2065) and Historic (1985–2015) of the Five LENS2 Ensemble Members Used to Generate Decarbonization Pathways

Index	LENS2 member ID	ΔT (°C)	ΔRH
1	r10i1191p1f2	2.50	−1.17
2	r5i1231p1f1	2.59	−1.79
3	r12i1301p1f2	1.70	0.10
4	r10i1181p1f1	2.03	−0.22
5	r9i1301p1f1	2.13	−0.80

Note. Index indicates the 1–5 label for each pathway that we use when presenting our results.

for each of these pathways by labeling them from 1 to 5 (Table 2). In using five sampled ensemble members, our purpose is to create heterogeneous decarbonization pathways that could all reach a given decarbonization target, then assess the pathways' vulnerabilities, trade-offs, and robustness. We do not create a pathway for each ensemble member because creating pathways that span all climate- and decarbonization-related uncertainty is not computationally tractable. Rather, researchers and practitioners explore a subset of this uncertainty in analyses and long-term plans. With respect to climate-related uncertainty, sampling algorithms are typically used to identify a few weeks of one weather year for inclusion in planning models. While these algorithms aim to capture periods that could threaten system resource adequacy, they capture a limited range of potential climate conditions, particularly when considering not just multiple weather years but also multiple climate realizations. We therefore demonstrate our framework in a similar context as is used in practice, that is, on pathways that consider a subset of relevant uncertainty. The CEM is programmed in the General Algebraic Modeling System (GAMS) (GAMS, 2024) and solved using CPLEX (IBM, 2024).

2.3. Decarbonization Pathways and Resource Adequacy Under Potential Climate Realizations

From our CEM, we obtain five decarbonization pathways, each planned for one of five sampled ensemble members. To understand the vulnerability of each decarbonization pathway to other potential ensemble members, we approximate the resource adequacy of each decarbonization pathway against all 100 ensemble members (or climate realizations) from LENS2. Because LENS2 provides daily values, we are unable to quantify resource adequacy (RA) of the Western Interconnect at an hourly basis using a standard probabilistic RA model. Instead, we approximate resource adequacy by quantifying daily Surplus Available Capacity (SAC) and Energy Not Served (ENS). While LENS2's daily resolution is a limitation of our study, LENS2 (and large ensembles generally) provide unique insights into extremes of varying timescales, from daily extremes like extreme heat to longer extremes like droughts (Deser et al., 2020; McKinnon & Simpson, 2022).

To calculate daily ENS, we run an economic dispatch model (EDM) for each decarbonization pathway output by our capacity expansion model in 2040. The EDM minimizes the sum of operating, CO_2 emission, inter-regional transmission, and ENS costs by optimizing generation, inter-regional transmission, and ENS decision variables. CO_2 emission costs include a decarbonization-pathway-specific CO_2 price necessary to achieve the relevant CO_2 emissions cap in that year. We determine this CO_2 price by iteratively increasing it until total CO_2 emissions comply with the cap. We include this price instead of a cap to avoid infeasibility in the EDM in climate realizations that preclude meeting the CO_2 cap. The EDM includes several constraints from the CEM, including balancing supply and demand within each of our five subregions while accounting for transmission inflows and outflows; constraining regional monthly hydropower generation to an energy budget; constraining wind and solar generation to spatially and temporally differentiated capacity factors; and constraining fossil-based thermal plant generation based on capacity deratings. Since we cannot probabilistically sample generator outages like hourly resource adequacy models, the EDM instead derates generators' capacities based on temperature-dependent or fixed forced outage rates (FORs). We run the EDM for a 1-year optimization horizon. Inputs to the EDM include a decarbonization pathway and variables driven by the given climate ensemble member (i.e., daily electricity demand, monthly hydroelectric generation, daily solar and wind capacity factors, and daily thermal plant forced outage rates and derates). See Text S6 in Supporting Information S1 for the full EDM formulation and key parameters. The EDM is programmed in Python (3.10.6), the optimization problem is formulated with Pyomo (6.4.2) (Hart et al., 2017) and solved using GLPK 5.0 (GNU, 2020).

From the EDM output, we directly obtain daily ENS and calculate SAC for each region. SAC equals daily available non-hydropower capacity, hydropower generation, and transmission imports minus demand and transmission exports for each region. In this way, SAC indicates excess supply available in a region to satisfy unexpected increases in demand. The lower the SAC, the greater the risk of a supply shortfall, suggesting lower resource adequacy. Prior research has used a net load metric as a proxy for resource adequacy (Ruggles & Caldeira, 2022; van der Wiel, Stoop, et al., 2019). Our SAC extends the net load metric by capturing not just daily wind and solar generation potential, but also accounts for optimized hydroelectric dispatch; temperature

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dependent outages in thermal and hydroelectric power plants; capacity deratings in fossil-based thermal power plants; and electricity flows between regions. See Text S7 in Supporting Information S1 for more details on SAC calculation.

2.4. LENS2 Climate Data and Conversion to Power System Variables

In the near-term (prior to 2050), internal variability (vs. model or emissions scenario uncertainty) is the primary source of climate-related uncertainty (Lehner et al., 2020; Schwarzwald & Lenssen, 2022). To capture the role of internal variability in driving potential climates through 2040, we use the CESM2 Large Ensemble (LENS2) (Rodgers et al., 2021). This data set is a single model initial-condition large ensemble (SMILE) following the SSP3-7.0 emissions trajectory. We treat this global emissions trajectory as independent of our system's emissions trajectory, as internal variability—not emissions uncertainty—s the primary source of uncertainty over our study period.

The LENS2 data set consists of 100 ensemble members which are split into 2 groups each consisting of 50 realizations, where each group is driven by one forcing condition. Each of the 50 realizations in the two groups are initiated from different initial conditions sampled to reflect micro and macro perturbations in the pre-industrial control simulation. Unless noted otherwise, all the variables with a specified frequency represent an average over the inherent time periods, for example, daily temperature is daily averaged temperatures and monthly runoffs are monthly averaged runoffs. We obtain daily surface temperature, 10 m wind speed, surface downwelling solar flux, surface atmospheric pressure, surface relative humidity, and monthly total runoff from 1980 to 2050 for each ensemble member. We obtain these variables at the highest spatial resolution possible, at a 100 km by 100 km grid. While this spatial and temporal resolution is lower than what is preferred for power system modeling, higher resolution climate data sets (e.g., from statistical or dynamical downscaling) often do not sample as large of a range of internal climate variability as LENS2 (Buster et al., 2022; Jones et al., 2022; Losada Carreño et al., 2020), particularly in the time-span of interest to us (through 2040) and when focusing on extreme events. On the other hand, this approach does not sample climate response uncertainty, that is, how different climate models portray the future response to greenhouse gas forcing. We discuss the value of using a large ensemble like LENS2 and how it can assist creation of higher resolution products in our Discussion. More information on LENS2 and our used variables are in Text S2 of Supporting Information S1.

We apply a mean bias correction to LENS2 surface temperatures using surface temperatures from the ERA5 reanalysis data (Hersbach et al., 2018; Maraun, 2016). To bias correct runoff for forecasting hydroelectric generation, we use a mean bias scaling method for each of the constituent drought regions (ref Text S2.4 in Supporting Information S1). More details on the bias correction methods are in Text S2.2 of Supporting Information S1. Other studies using large ensembles for quantifying climate impacts have also used such mean bias correction methods (Schwarzwald & Lenssen, 2022). We do not use more sophisticated bias correction methods like quantile mapping (QM) as it fits the distribution of projections to observations (historical climate), which may lead to loss of changes in internal variability in the projections. We do not find a strong bias in solar radiation, so we did not bias correct it. Though we identify biases in 10 m wind speeds relative to ERA5, wind power capacity factors derived from bias corrected wind speeds are much lower compared to other observational data sets. As a result, we use the native LENS2 wind speed data in our analysis.

We use different models to derive power system variables from LENS2 data. We calculate daily solar and wind capacity factors for each LENS2 grid cell using deterministic equations (Text S2.3 in Supporting Information S1). We calculate monthly hydroelectric generation using a linear regression model using total runoff as the predictor variable. We obtain the model for each drought region in the Western US (Turner, Voisin, Nelson, & Tidwell, 2022) by training observed hydroelectric generation (Turner, Voisin, & Nelson, 2022) trained against ERA5 total runoff. We then forecast hydroelectric generation using bias corrected total runoff from the LENS2 data (Text S2.4 in Supporting Information S1). We calculate demand for each of our five subregions using a piecewise linear regression model using daily temperature as the predictor variable. The regression model is trained using observed demand data and ERA5 surface temperatures, so ignores technological or population changes (Text S3 in Supporting Information S1). We calculate temperature-dependent forced outage rates for thermal power plants using plant-type-specific relationships (Murphy et al., 2019) (Text S4 in Supporting Information S1). We also calculate capacity deratings of fossil-based thermal power plants for each LENS2 grid cell using plant-type-

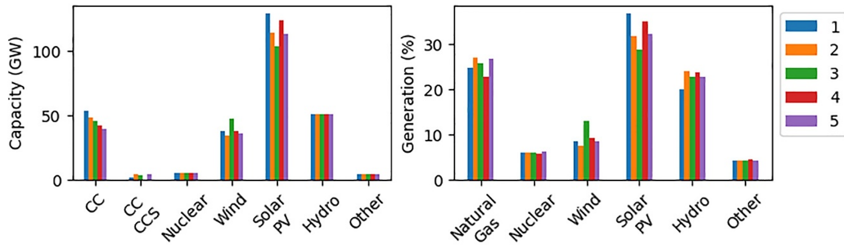

Figure 2. Installed capacity (left) and electricity generation (right) by generator type across Western Interconnect in 2040 for each of our five decarbonization pathways (Table 2). CC stands for natural gas combined cycle, CCCCS for CC with carbon capture and sequestration, and PV for photovoltaic. Other includes biomass, geothermal, landfill gas, and fossil and non-fossil waste plants.

specific relationships between deratings and air temperatures, relative humidity, and/or air pressure (Text S4 in Supporting Information S1).

3. Results

3.1. Capacity Investments Across Decarbonization Pathways

We first examine the five decarbonization pathways output by our capacity expansion model. In creating these pathways using five sampled LENS2 ensemble members rather than creating 100 pathways using each of the 100 LENS2 ensemble members, we demonstrate the value of our framework in analyzing a limited number of alternatives generated by computationally complex planning models, similar to how alternatives are incorporated in system planning in practice. Each pathway is defined by its "fleet" of energy generator types. Our pathways decarbonize primarily through investment in wind and solar capacity, but exhibit different levels of investment (Figure 2). Interconnect-wide solar and wind capacity increase from roughly 40 and 30 GW in 2022, respectively, to up to 129 and 46 GW in 2040, respectively, across pathways. Between pathways, wind and solar capacities in 2040 range from 34 to 46 GW and from 103 to 129 GW, respectively. Small amounts (less than 4 GW) of NGCC with carbon capture and sequestration (CCS) are also deployed in four decarbonization pathways. Heterogeneity in solar and natural gas capacity largely drives differences in total installed capacity between pathways, which ranges from 252 to 280 GW. Solar capacity investment largely occurs in three regions—California, Desert Southwest, and Central—with high quality solar resources, while wind investment largely occurs in the Northwest, which has high quality wind resources (Figure S1 in Supporting Information S1). No investment in interregional transmission beyond existing capacity occurs. Growth in wind, solar, and NGCC capacity displace other capacity, including coal-fired capacity, and replace lost capacity from the retirement of the Diablo Canyon nuclear generating station, which is located in California. Generation by plant type follows similar trends as capacity investments. Across pathways, wind, solar, natural gas, and hydropower account for roughly 7%–13%, 31%–37%, 23%–27%, and 20%–24% of annual generation, respectively, in 2040.

3.2. Resource Adequacy of Decarbonization Pathways Under Future Climate Realizations

For each decarbonization pathway, we use LENS2 to quantify daily electricity supply and demand under 100 potential climate realizations in any given year. Using daily supply and demand, we approximate resource adequacy through two metrics: daily surplus available capacity (SAC) and daily energy not served (ENS), both quantified in units of electricity. SAC indicates excess electricity supply available in a region to satisfy unexpected increases in demand, while ENS equals the difference between electricity demand and supply. A negative daily SAC value indicates ENS occurs, while larger positive SAC values indicate greater redundancy against supply shortfalls. ENS is rare in power systems, as it results in voluntary or involuntary load shedding. Involuntary load shedding occurs during rolling blackouts. Given daily SAC and ENS for each of our five decarbonization pathways under each of our 100 ensemble members, we then calculate the annual minimum SAC ("minimum SAC"), which indicates the fleet's largest susceptibility to supply shortfalls in a given year, and total annual ENS ("total ENS"), which indicates the fleet's total supply shortfall in a given year.

Figure 3 and Figure S2 in Supporting Information S1 show these two metrics for the regions in the Western Interconnect in 2040. Depending on the region, resource adequacy failures occur in most or all decarbonization

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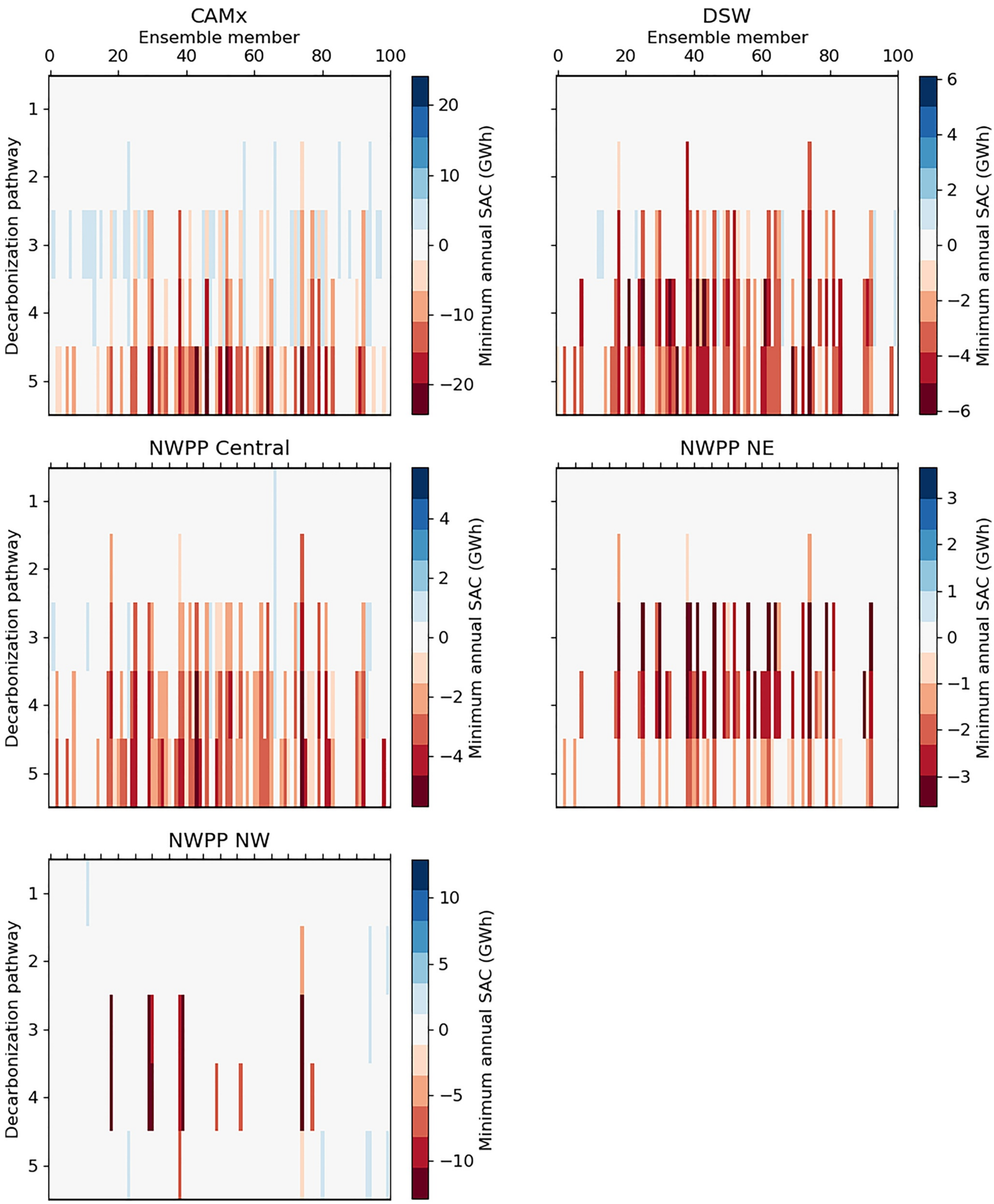

Figure 3. Minimum annual SAC values for each subregion in 2040 (see Figure 1 for map of regions). Each panel corresponds to a realization of the "Surplus available capacity" panel of Figure 1. Each row corresponds to one of our five decarbonization pathways. Within each row, there are 100 separate color bars that indicate that pathway's minimum annual SAC against each of our 100 climate ensemble members. Minimum annual SAC values range from negative (red) to positive (blue) red values indicate supply shortfalls (or resource adequacy failures), while blue values indicate surplus capacity relative to demand.

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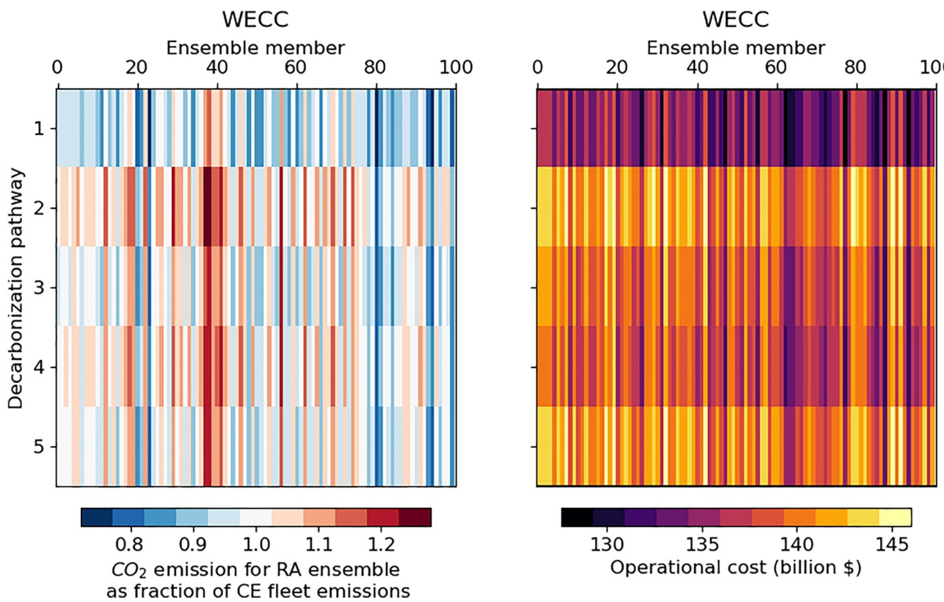

Figure 4. Same structure as Figure 3, but each color bar shows interconnect-wide CO_2 emissions as a fraction of the target CO_2 emissions cap (left) or interconnect-wide operational costs (right) in 2040.

pathways under many climate realizations, as indicated by negative SAC values and positive total ENS values. Pathways exhibit significant differences in resource adequacy under future climate realizations. For instance, in California in 2040, one decarbonization pathway (5, or the pathway generated using the r9i1301 climate ensemble member) has a maxiumum of 286 GWh of total yearly ENS, whereas the other pathways have maximum total yearly ENS of 0–100 GWh, respectively. The pathway with the least ENS and greatest SAC—r10i1191 (or 1 in Figure 5)—achieves more installed capacity in 2040 (280 GW) relative to other pathways (251–262 GW), particularly through greater investment in solar PV and natural gas combined cycle (Figure 2). Across decarbonization pathways, certain climate realizations incur significantly greater ENS than others (as indicated by vertical red stripes). For instance, of the total ENS across all 2040 California pathways and all 100 climate realizations, none of that ENS occurs in 79% of climate realizations, while 50% of that ENS occurs in just 3% of climate realizations. Maximum ENS values are driven by days with low hydropower, coinciding low wind and solar generation, and high electricity demand (Figures S4–S8 in Supporting Information S1), indicating an important role of compounding extremes in driving resource adequacy failures (Craig et al., 2020; Turner et al., 2019).

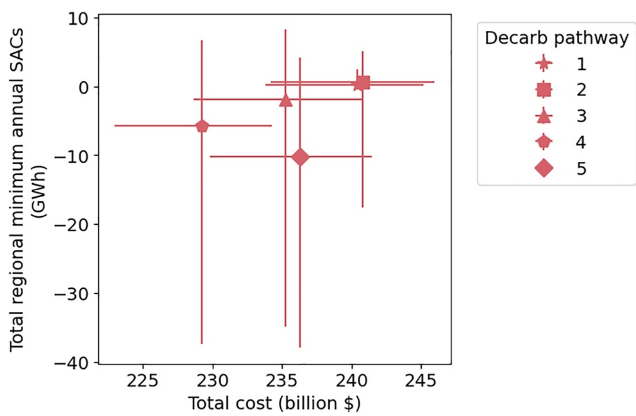

Figure 5. Sum of minimum annual SAC values for our five subregions in 2040 versus cumulative (2023–2040) total (fixed plus operating) costs for each decarbonization pathway. Minimum annual SAC values equal the sum of non-synchronous subregional minimum SAC values. Each decarbonization pathway is depicted with a cross; the dot at the center of each cross indicates the mean total SAC and mean total cost for that decarbonization pathway across all 100 climate ensemble members; the horizontal arm of each cross ranges from the minimum to maximum total cost for that decarbonization pathway across all 100 climate ensemble members; and the vertical arm of each cross ranges from the minimum to maximum total SACs for that decarbonization pathway across all 100 climate ensemble members. For context, total non-synchronous peak demand across the five subregions equals roughly 200 GWh (although peak demand varies across climate realizations). A negative minimum annual SAC value indicates one or more subregions in that pathway experiences a supply shortfall under at least one future climate realization.

3.3. Carbon Dioxide Emissions and Costs of Decarbonization Pathways Under Climate Realizations

Future climate variability will affect not only the resource adequacy of future fleets, but also their CO_2 emissions and operational costs through changes in electricity demand; available wind, solar, and hydropower potential; and generation from dispatchable (largely fossil) plants (Figure 4). Across our decarbonization pathways, climate realizations could result in CO_2 emissions higher or lower than the CO_2 cap by up to 28% and 27%, respectively. As with resource adequacy (Figure 3), CO_2 emissions from some decarbonization pathways are less vulnerable to climate variability than others. For instance, one pathway (2, or generated using the r5i1231 climate ensemble member) fails to meet the CO_2 emissions cap in 70% of climate realizations, while another pathway (1) only fails to meet the emissions cap in 20% of realizations. Operational costs also vary across climate realizations in each pathway, from \$127 to \$146 billion. No single meteorological variable drives the observed variability in emissions and costs (Figure S9 in Supporting Information S1). Rather, high emissions generally occur in climate realizations with low wind, solar, and hydropower generation and high demand.

3.4. Trade-Offs Between Resource Adequacy and Costs

Power system planners must balance competing objectives of minimizing system costs while meeting resource adequacy targets. Figure 5 compares each decarbonization pathway's total costs against the sum of annual minimum SAC over the five sub-regions (Figure 3) across 2040 climate realizations. Total costs include fixed investment costs, which vary between decarbonization pathways but not climate realizations, and operational costs (Figure 4), which vary between decarbonization pathways and climate realizations. Cumulative total costs from 2023 to 2040 range from \$223–246 billion across pathways and climate variability. Although pathways are differentiated by their mean costs across realizations, variability in operational costs induced by climate variability introduces overlap in total cost ranges between pathways. Despite overlaps between total costs, pathways can exhibit significant differences in resource adequacy outcomes. For instance, one pathway (1, or the first pathway from the right in Figure 5) only exhibits a small resource adequacy failure (or a total regional minimum annual SAC value of −0.2 GWh) under one climate realization, and has a positive mean SAC value across ensemble members. Other pathways (e.g., the three pathways at left in Figure 5) have larger resource adequacy failures (of up to −40 GWh SAC) under certain ensemble members, and negative mean SAC values across ensemble members (of up to −10 GWh). Selecting the first pathway rather than other pathways would eliminate resource adequacy failures at a median total cost difference of −1 to 3%.

3.5. Identifying an Alternative Decarbonization Pathway Robust to Future Climate Realizations

Our prior results indicate a subset of potential climate realizations drive significant risk of resource adequacy failures across decarbonization pathways (Figure 3). We identify the ensemble member that drives the largest resource adequacy failures (quantified as the sum of minimum annual SACs) across decarbonization pathways in California (our largest load region) in 2040, namely r19i1231 (or pathway 6), then rerun our capacity expansion model using that ensemble member's meteorology. This ensemble member was not captured in our initial sampling procedure, in which we selected five ensemble members that spanned the warming at mid-century represented by the ensembles in the CESM2-LE data set (Figure S12 in Supporting Information S1). Rather, r19i1231 features a compound extreme event in 2040 of low hydropower and wind generation potential and high air temperatures, the latter of which drive elevated electricity demand and low available thermal capacity (Figure S11 in Supporting Information S1). Capturing unexpected extreme climate realizations, such as r19i1231, is a key motivator for our framework, as identifying extremes a priori is difficult given complex interactions within power systems.

Our new decarbonization pathway generated with the r19i1231 climate ensemble member invests in more solar and NGCC capacity and in less wind capacity than other pathways (Figure 6a). Overall, capacity investment is 2–30 GW greater in the new pathway than other pathways. Figure 6b compares the resource adequacy of the decarbonization pathway generated with this new ensemble member versus our original decarbonization pathways. Our new pathway exhibits significantly higher minimum SAC values, indicating less vulnerability to resource adequacy failures. In fact, the new pathway does not experience any resource adequacy failures across any climate realizations in 2040 in any region (i.e., no ENS or negative SAC values), and has a minimum annual SAC of 0–3 GWh in California across climate realizations. The newly generated pathway also meets CO_2 emission caps in all but three potential climate realizations (Figure 6c). Figure 6d compares the trade-off between resource adequacy and system costs for the new versus prior pathways. The new pathway has significantly better resource adequacy than prior pathways, but at greater total costs. Specifically, the new pathway incurs, on average, roughly \$10 billion greater total costs between 2023 and 2040 compared to the next costliest pathway.

4. Discussion

Existing research and system planning practices lack decision support frameworks for identifying investment alternatives that are robust to climate-related uncertainty. We construct such an analytical framework by integrating planning and operational power system models with a large climate ensemble, then use our framework to

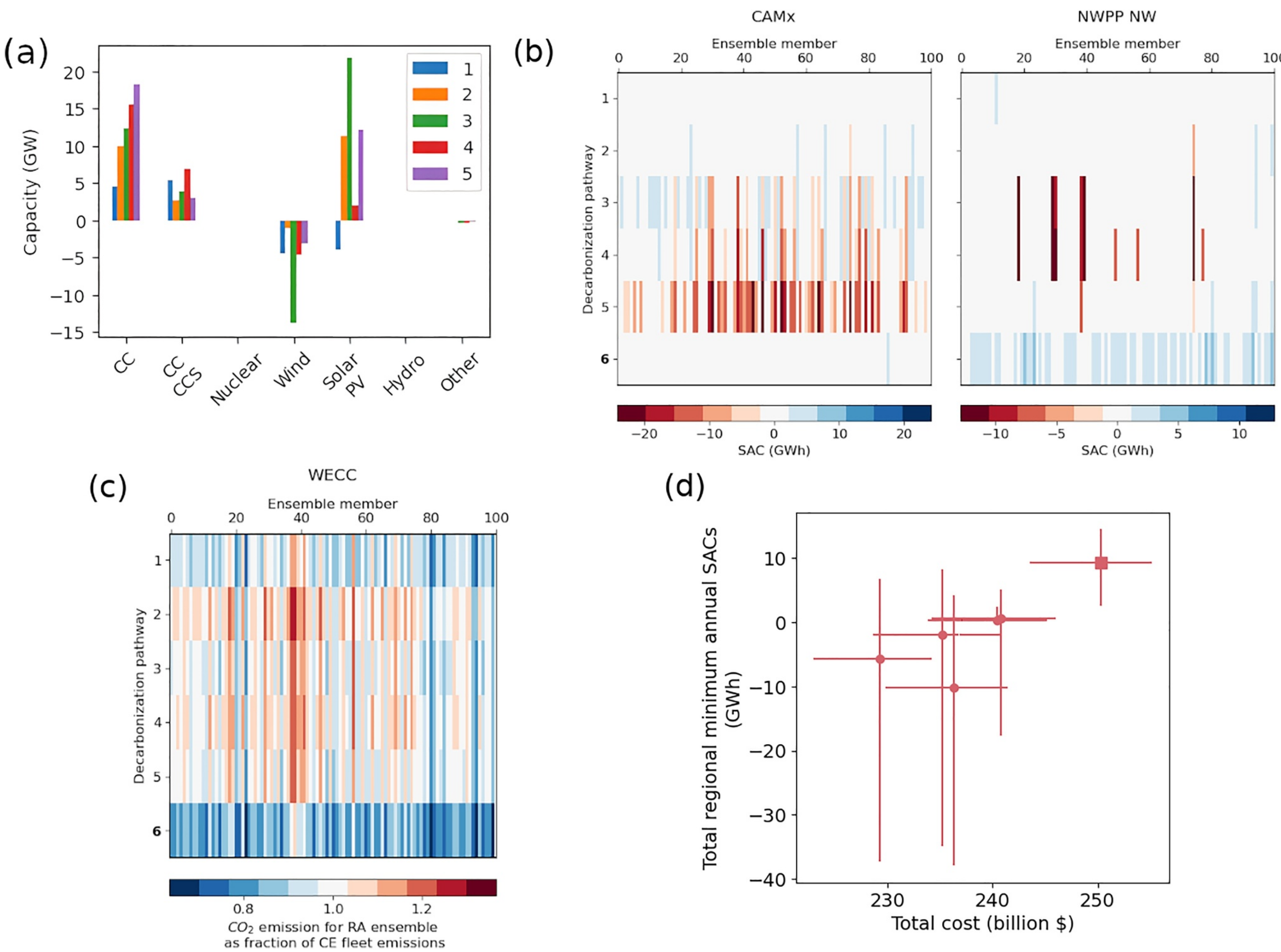

Figure 6. (a) Difference in installed capacity by generator type across Western Interconnect in 2040 between the decarbonization pathway generated using the r19i1231 ensemble member (pathway "6") and each of the other decarbonization pathways. CC stands for natural gas combined cycle, CCCCS for CC with carbon capture and sequestration, and PV for photovoltaic. (b) Same structure as Figure 3, but includes the decarbonization pathway generated using the r19i1231 ensemble member (pathway "6") (bolded at bottom) and only includes the two largest subregions by demand for conciseness. (c) Same structure as left panel of Figure 4, but includes the decarbonization pathway generated using the r19i1231 ensemble member (pathway "6") (bolded at bottom). (d) Same structure as Figure 5, but includes the decarbonization pathway generated using the r19i1231 ensemble member (shown as cross centered on square instead of circle).

identify the vulnerabilities, trade-offs, and robustness of alternative decarbonization pathways for the Western U. S. power system in 2040. We began our analysis with five alternative pathways to 60% decarbonization of the power system. All of these pathways exhibited modest to significant resource adequacy failures under potential climate realizations. But by choosing one pathway over others, significantly better resource adequacy outcomes can be achieved at little additional cost. Even this more robust pathway, though, suffered resource adequacy losses under future climate realizations. By identifying a particularly problematic future climate realization for future resource adequacy and using it to create another alternative decarbonization pathway, we identified a pathway robust to, or that experienced no resource adequacy failures under, all examined future climate realizations. This robustness is achieved through an increase of roughly $10 billion (or 5%) in total costs, posing a trade-off to decision-makers.

Our analysis quantifies the resource adequacy of alternative decarbonization pathways against a wide range of near-term climate variability. Capturing this range of climate variability was possible through the use of the LENS2 data set, but came at the cost of climate data with poor spatial and temporal resolution. Energy system modeling needs and available climate data set characteristics are often misaligned (Craig et al., 2022), and conducting detailed downscaling of all LENS2 ensemble members is computationally prohibitive. However, our analytical framework can guide high resolution downscaling of large climate ensembles like LENS2 for energy system applications, a key need for energy system modelers. Specifically, our framework can identify ensemble members, periods of interest, and/or climate conditions that pose the greatest threat to alternative future power systems. Threatening conditions are themselves a function of investment decisions in power systems, so identifying those conditions for a broad range of alternatives, as our framework enables, is crucial to fully characterize vulnerabilities and robustness. In our case, one ensemble member (r19i1231) resulted in resource adequacy failures across nearly all studied decarbonization targets due to the compounding effects of low wind and hydropower generation potential and high air temperatures. Identified members, periods, or climate conditions of concern can be selectively downscaled and fed back into planning or resource adequacy modeling, maximizing the value of high resolution downscaled data. This process requires bottom-up trans-disciplinary collaboration between energy system and climate modellers (Craig et al., 2022).

In using climate data with poor temporal (daily) resolution, our analysis suffers from two shortfalls. First, we are unable to capture the diurnal pattern of solar power in which it does not generate power at night, potentially biasing our investment decisions and resource adequacy analyses in favor of solar power. Second, because we do not resolve periods within the day, we are unable to include intra-day electricity storage in our planning or resource adequacy modeling. Intra-day storage, particularly utility-scale lithium-ion facilities, is a rapidly growing source of grid capacity and flexibility, particularly in California (Antonio & Mey, 2024; US Energy Storage Monitor—Q1 2024 and 2023 Year in Review Executive Summary, 2024). This flexibility and capacity could provide valuable when adapting to climate change and increasing intensity and frequency of extreme weather events. While our LENS2 climate data set is unable to capture this value, implementation of our framework per the above guidelines would enable stakeholders to capture the value of storage for climate adaptation. Daily resolution could also explain the lack of investment in interregional transmission capacity, since short-term (sub-daily) peaks in wind and solar generation drive value for expanded inter-regional transmission. Prior research on decarbonization scenarios for the Western United States using high resolution historic weather data finds significant transmission expansion in cost-optimal futures (Brown & Botterud, 2021; Jenkins et al., 2021).

Additional opportunities for extending our research exist. We do not consider changes in demand due to adoption of new technologies, for example, heat pumps to electrify space heating or space cooling in response to increasing temperatures. In winter peaking regions like the Northwest, electrified heating through heat pumps can lead to higher demand in the winter months, introducing interactions between decarbonization and climate change that could affect our SAC calculations. In the Northwest and other regions with historically low space cooling penetrations, adoption of space cooling could also interact with increasing extreme heat to exacerbate summer peak demands. Incorporating the effect of such demand-side changes in our models will allow us to make accurate assessment of future fleets' robustness (Wessel et al., 2022). Future research could also extend our framework to incorporate additional robustness concepts. For instance, in practice utilities design future systems that meet certain resource adequacy thresholds, for example, the 1-in-10 standard, which could be captured using a satisficing metric. While we focus on the year 2040 when assessing resource adequacy of alternative systems against potential climate realizations, future research could also consider the temporal evolution of system outcomes under climate change. Doing so could illuminate trade-offs in the near-to long-term of decarbonization pathways to climate change. Our framework could also be extended to planning of other power systems in the United States and globally, which will also grapple with climate-change-driven impacts on demand and supply (Yalew et al., 2020). Specific insights, though, will vary given region-specific contexts that will moderate impacts of climate change, for example, regions will vary in their reliance on hydropower and need for space heating and/or cooling.

Our framework provides a practical way for real-world system planners and utilities to better account for climate-related uncertainty, whether planning for individual or multiple regions in the Western United States or elsewhere. Regulators could also require system planners to use our framework during Integrated Resource Plan (IRP) proceedings to understand trade-offs between improved resource adequacy and greater consumer costs. Many system planners use third-party software, for example, PLEXOS, to make long-term plans. Modifying the underlying mathematical formulation of such software is challenging for end users. Instead, our framework requires changes to model inputs and additional processing of model results, a more feasible undertaking. The key element of our analytical approach is to stress test alternative investment plans (or decarbonization pathways) against potential climate realizations to identify system vulnerabilities and challenging climate conditions, then feed identified challenging conditions back into decisionmaking. Energy system planners will use planning processes that diverge from our methods in several ways. Despite these differences, planners can adopt the key element of our analysis into their planning processes to better deal with climate-related uncertainty by following these guidelines. First, planners should identify a range of climate realizations of interest, ideally in collaboration with climate scientists. These realizations will likely have higher resolution than our LENS2 climate data set, requiring planners to sample periods to include in their planning model given computational constraints. Planners can adapt their sampling procedures or adopt new procedures designed for future climate data (Hilbers et al., 2019). In either case, sampled time periods will not capture the full range of weather conditions that could affect future power systems. Stress testing alternative decarbonization pathways to the full range of weather, the key element of our framework, can therefore generate crucial insights into system vulnerability when sampling time periods for planning. Second, planners should analyze alternative decarbonization pathways that stem not from climate variability, but instead from other sources of uncertainty that they typically focus on, for example, policy, emissions reduction target, or technology availability. With our framework, planners can understand vulnerabilities of these alternative pathways to future climate change. Third, planners can feed identified vulnerabilities and meteorological drivers of those vulnerabilities back into their planning process, for example, as additional sampled periods, to identify more robust investment strategies. Finally, our framework can illuminate investment pathways robust to climate change, but investment strategies should be coupled with adaptive planning (Marchau et al., 2019) to ensure continued robustness under climate uncertainty. By following these guidelines, our framework can help stakeholders identify future power systems that are robust to climate change and that simultaneously advance reliable, affordable, and clean objectives.

Data Availability Statement

Meteorological data used in this study is available through (Rodgers et al., 2021). Code for the CEM, SAC calculations, and analysis notebook used to create figures in the manuscript are available at (Sundar & Craig, 2024a). Input data to various models and analysis data is available at Zenodo (Sundar & Craig, 2024b).

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