

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

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935 tion

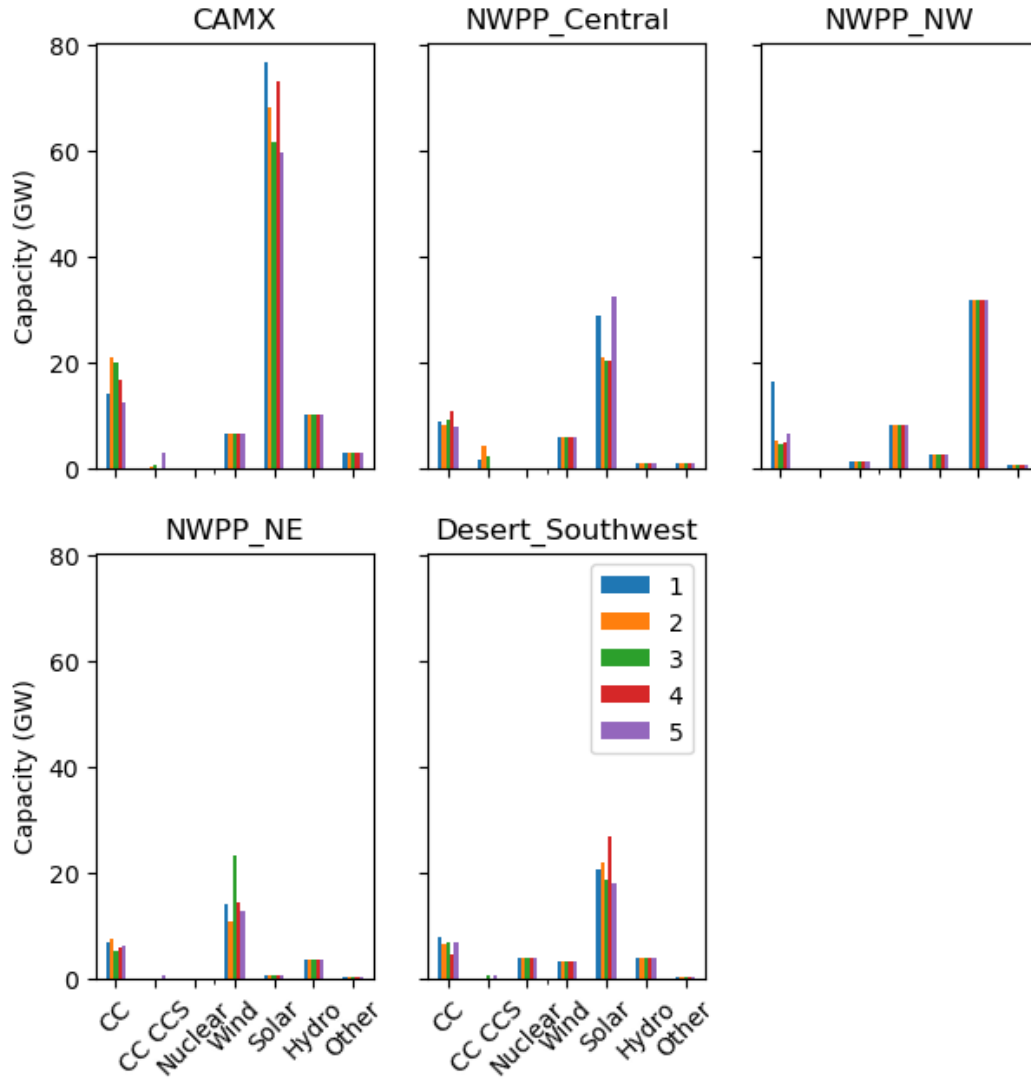
S1 Results

Figure S1: Installed capacity of each generator type across each subregion in WECC in 2040. CC = natural gas combined cycle; HD = hydropower; and NU = nuclear. Other includes biomass, geothermal, landfill gas, and fossil and non-fossil waste plants. CAMX stands for California and Mexico (we do not model Mexico), and NWPP stands for Northwest Power Pool; for a map of regions, see Fig. 1.

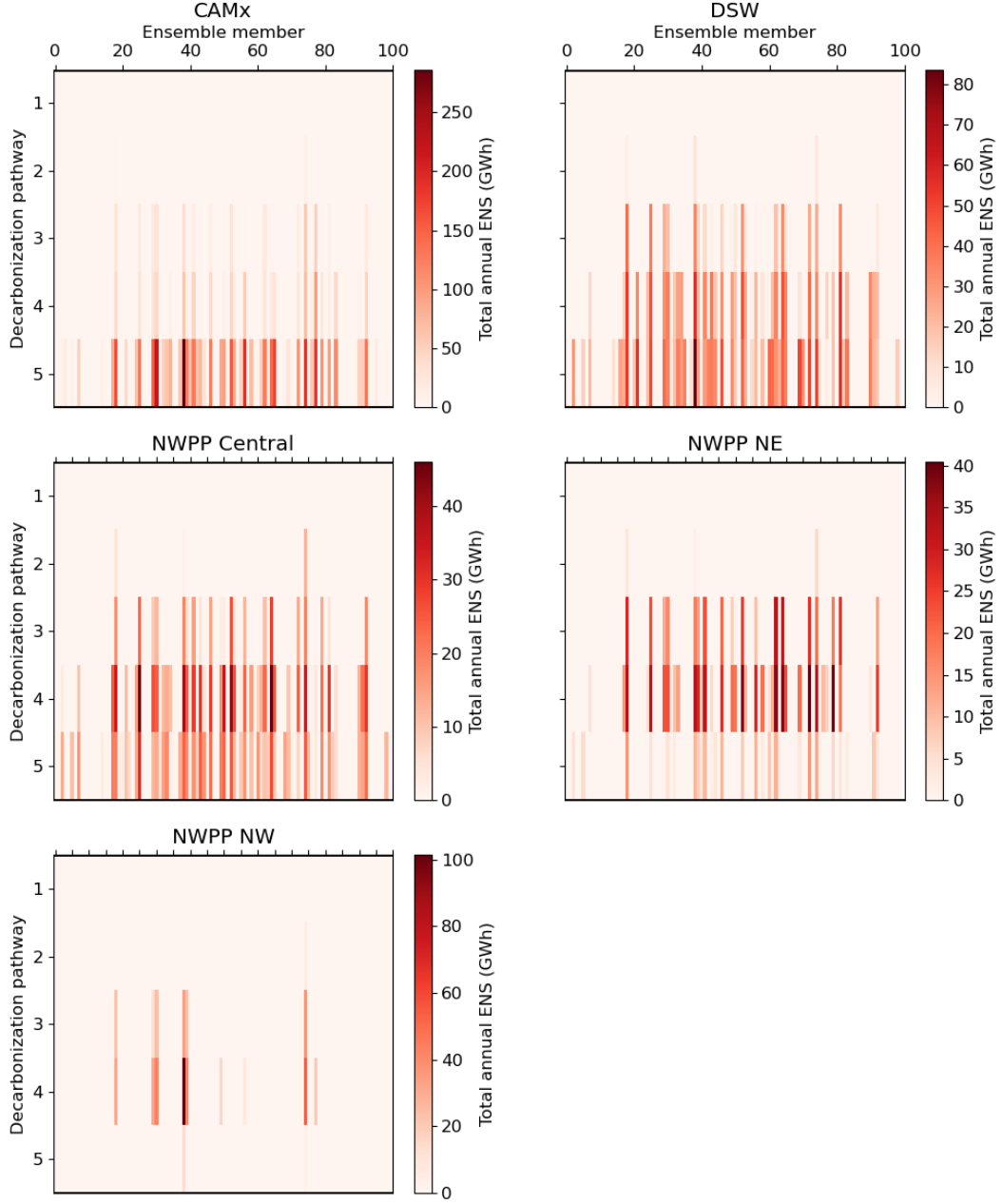


Figure S2: Total annual energy not served (ENS) for each subregion in 2040. Each row corresponds to one of the five decarbonization pathways. Within each row, there are 100 separate color bars that indicate that pathway's total annual ENS against each of our 100 climate ensemble members.

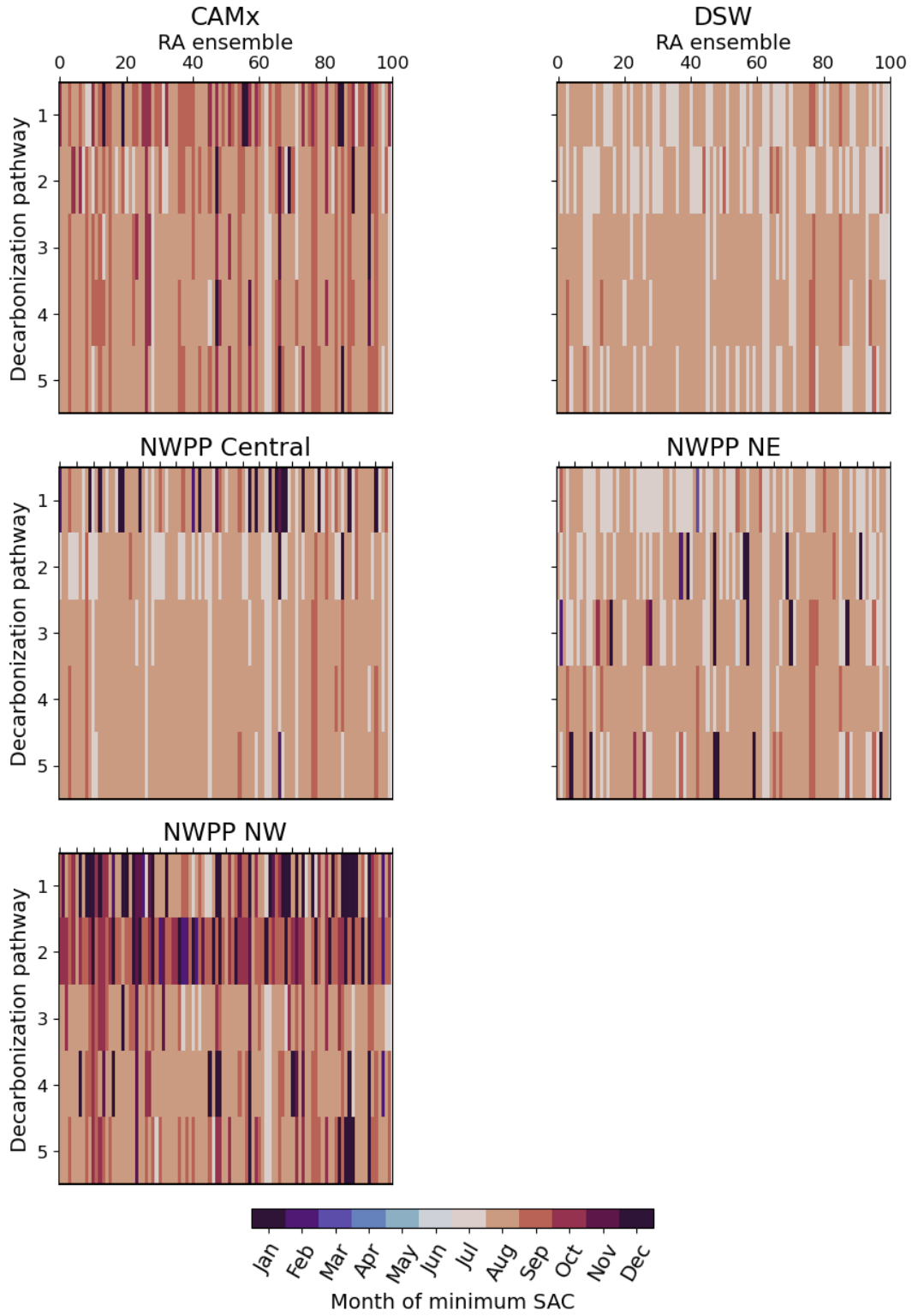


Figure S3: Month when minimum annual SAC occurs for each subregion in 2040. Each row corresponds to one of the five decarbonization pathways. Within each row, there are 100 separate color bars that indicate the month when that pathway's minimum SAC occurs against each of our 100 climate ensemble members.

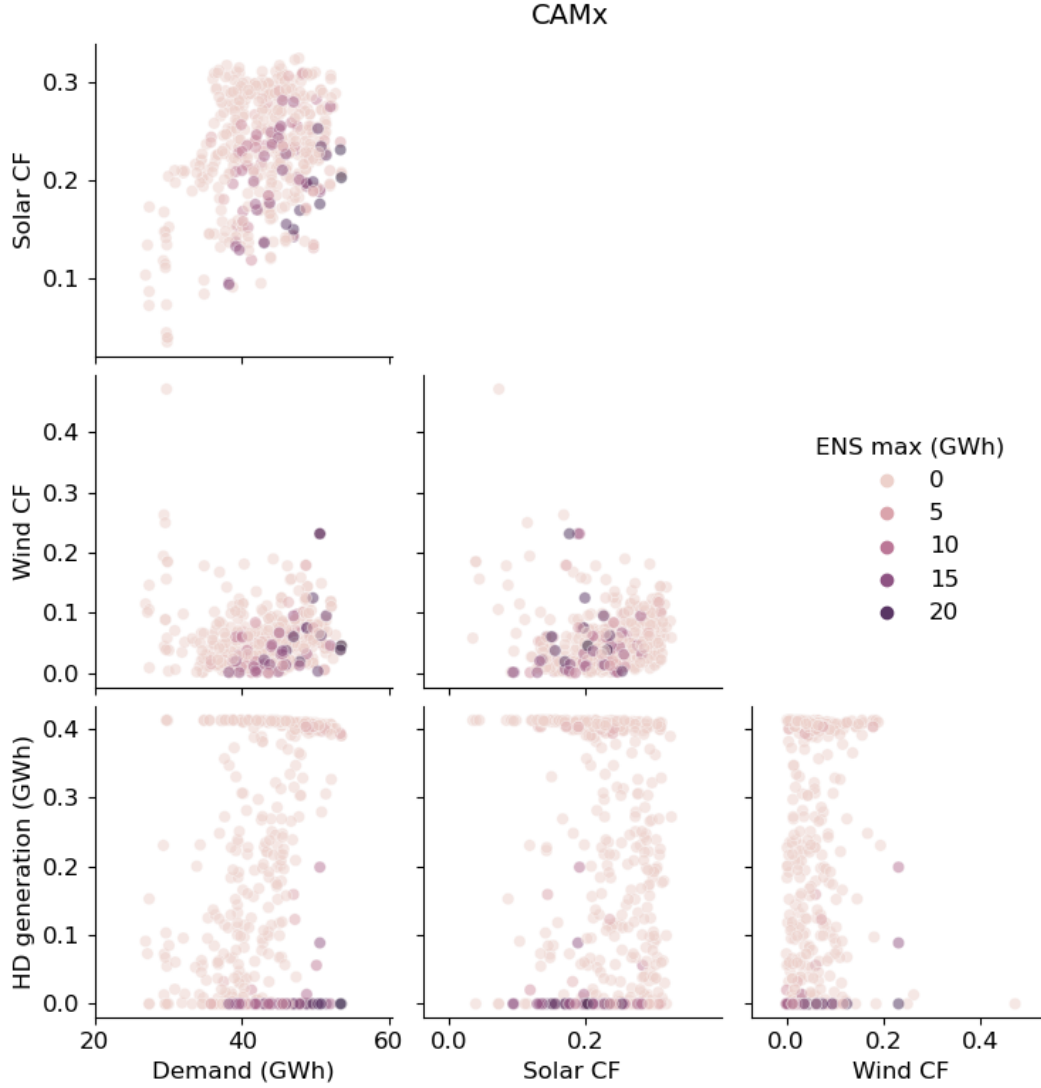


Figure S4: Pair plots of weather-driven energy system variables, namely daily electricity demand, solar and wind capacity factors (CF), and hydropower (HD) generation, in California (or our CAMx subregion) in 2040 on the day with the highest annual energy not served. Each plot contains 500 points, which correspond to each of our five initial decarbonization pathways run against each of our 100 ensemble members. Colors indicate ENS magnitude.

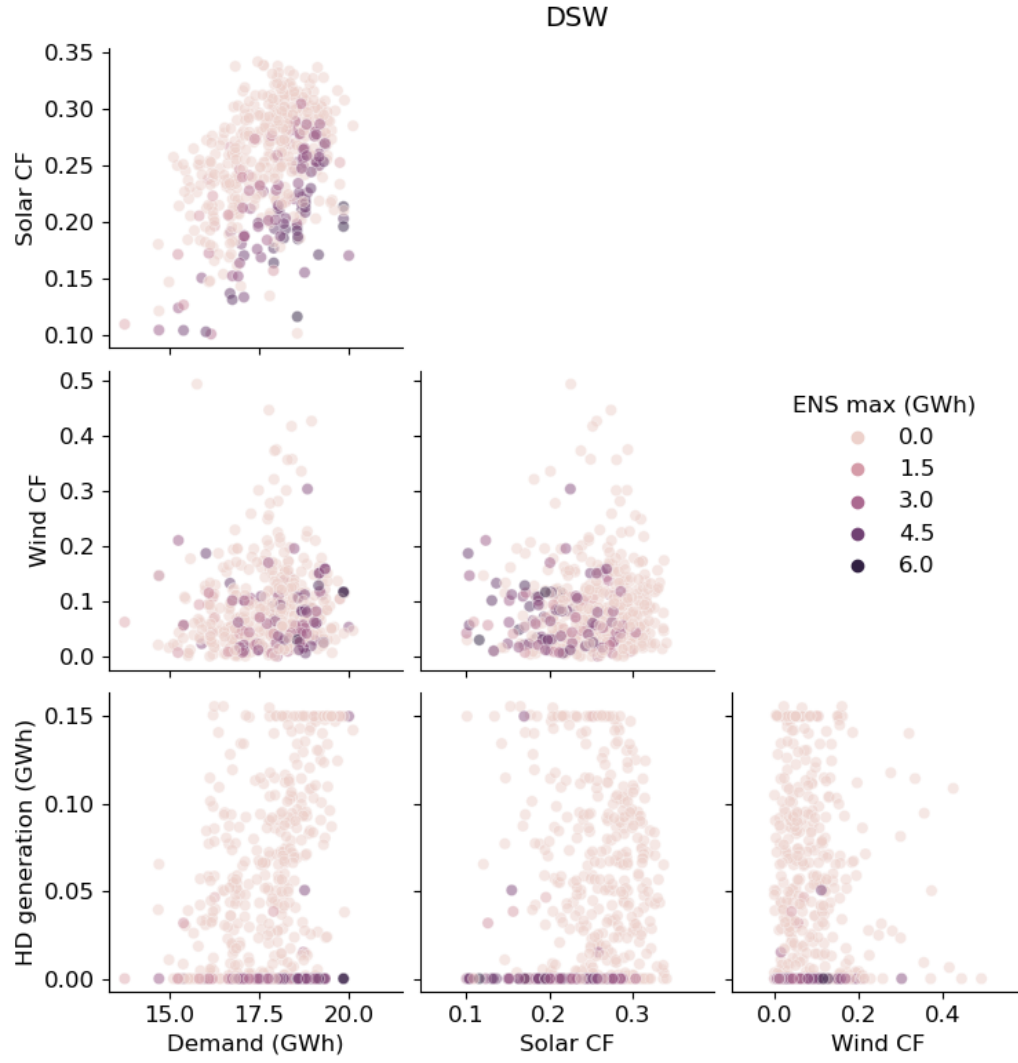


Figure S5: Same as figure S4 but for the Desert Southwest.

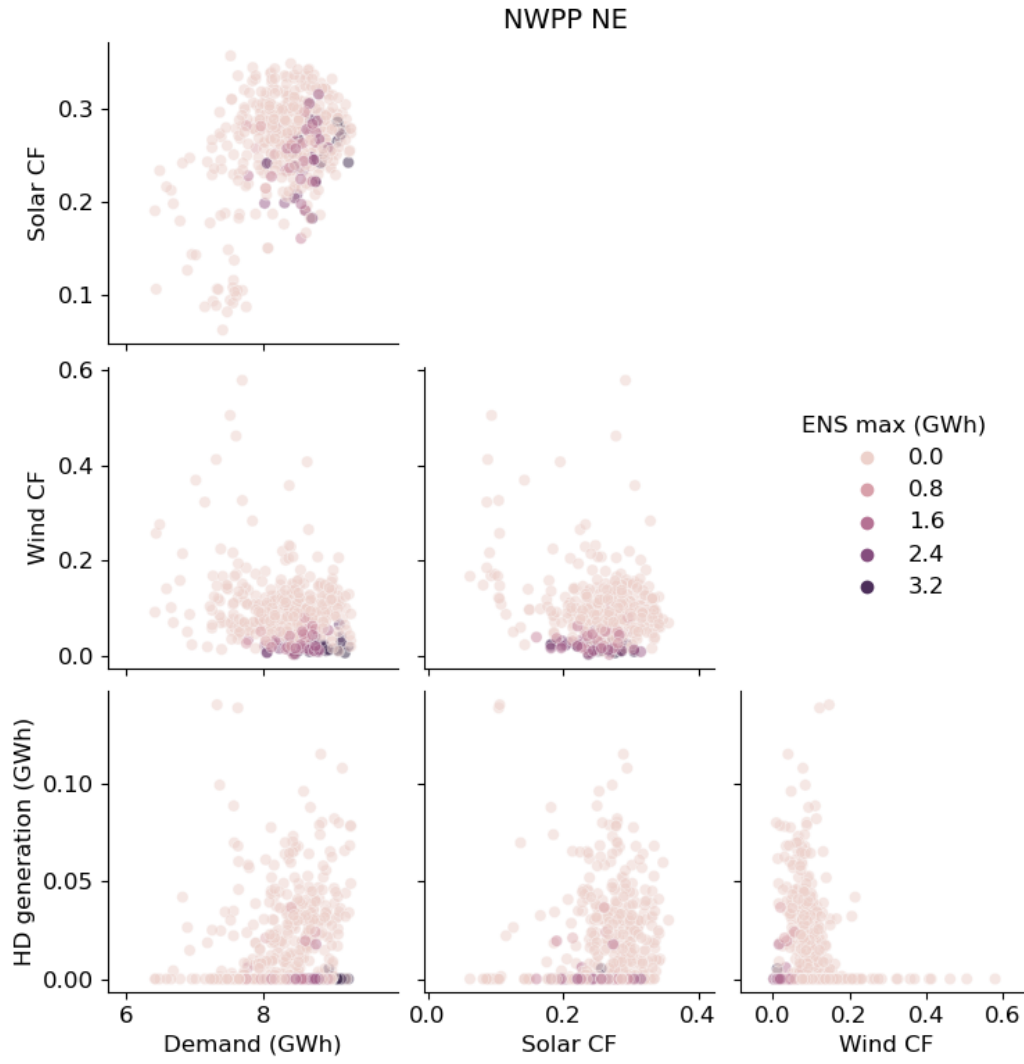


Figure S6: Same as figure S4 but for NWPP NE subregion.

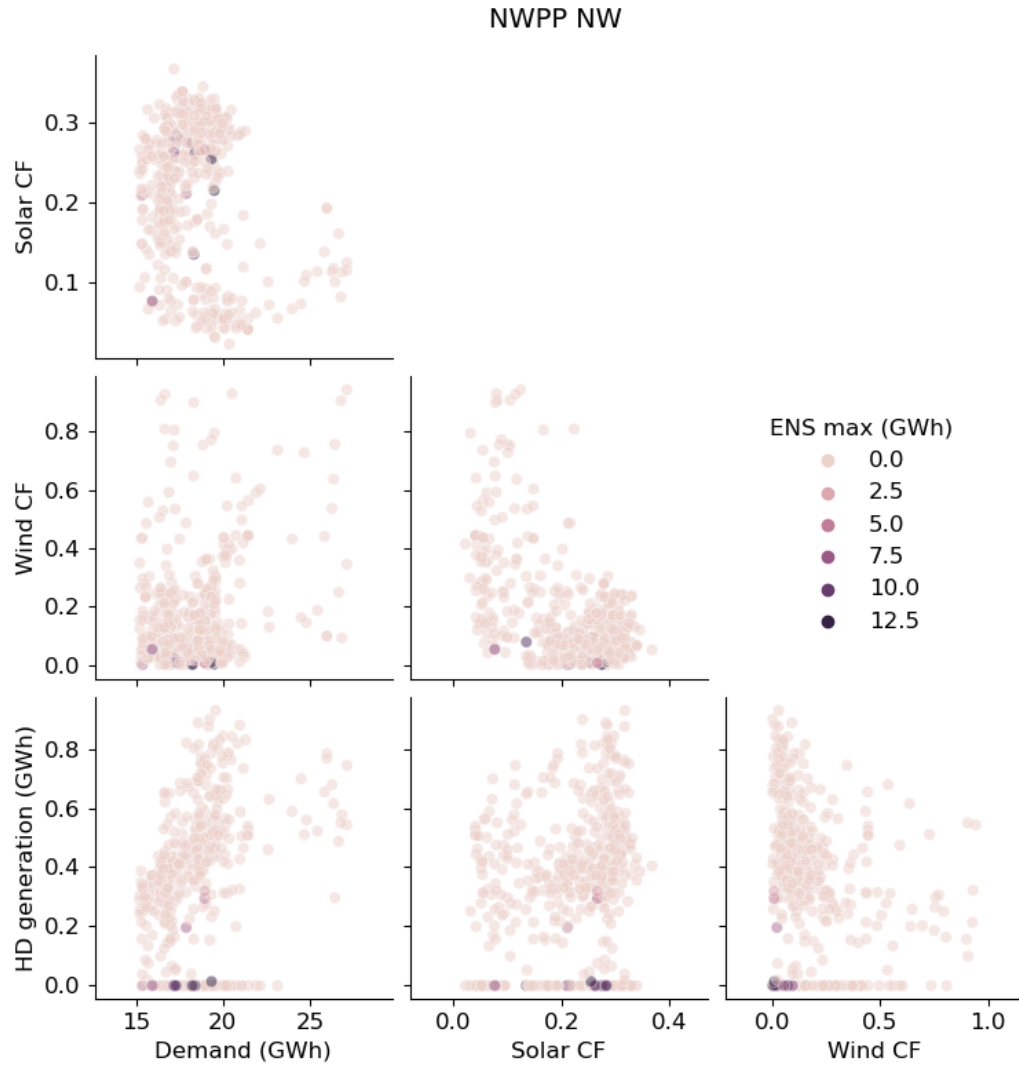


Figure S7: Same as figure S4 but for NWPP NW subregion.

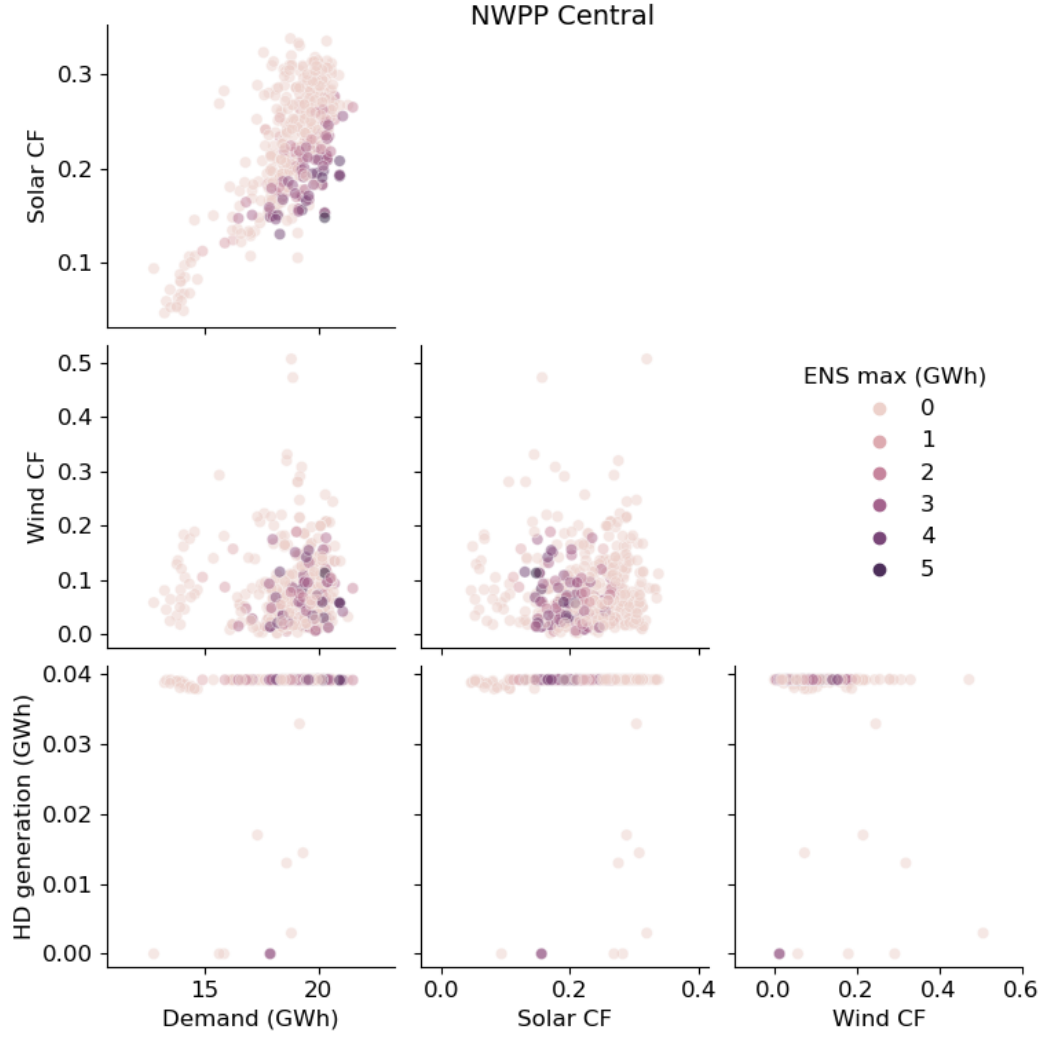


Figure S8: Same as figure S4 but for NWPP Central subregion.

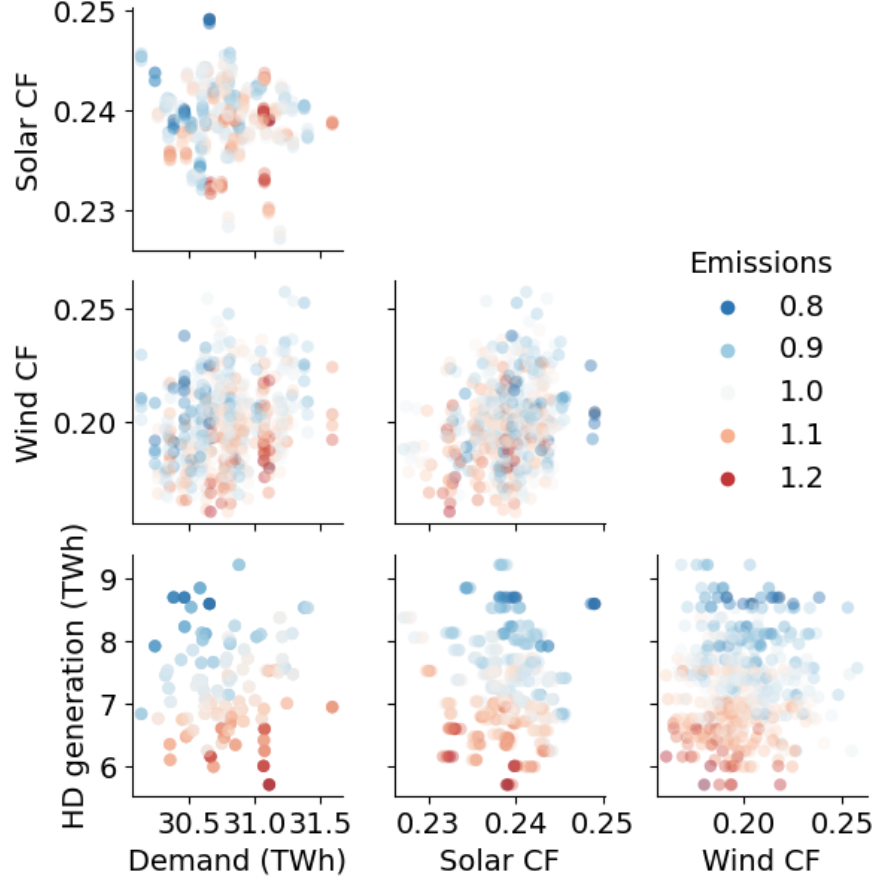


Figure S9: For our five initial decarbonization pathways evaluated against all ensemble members for the whole WECC region, this shows pair plots of weather-driven energy system variables: annual average solar capacity factors (CFs), annual average wind CFs, total annual demand, and total annual hydroelectric generation. Points are colored by annual CO₂ emission fractions normalized against the 40% emissions target. Emissions tend to exceed the intended cap in ensemble members with low hydropower generation and coinciding low wind and solar resources.

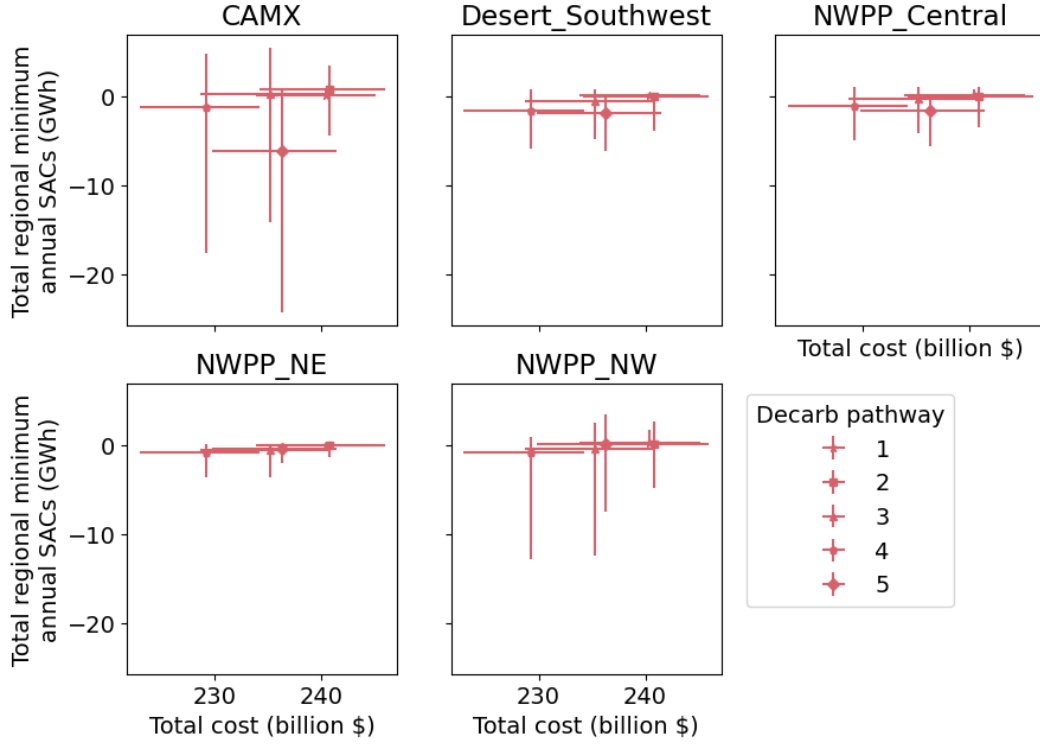


Figure S10: Sum of minimum annual SAC values for each of our five subregions in 2040 versus cumulative (2023-2040) total (fixed plus operating) costs for each decarbonization pathway. Minimum annual SAC values equal the sum of non-synchronous subregional minimum SAC values. Each decarbonization pathway 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.

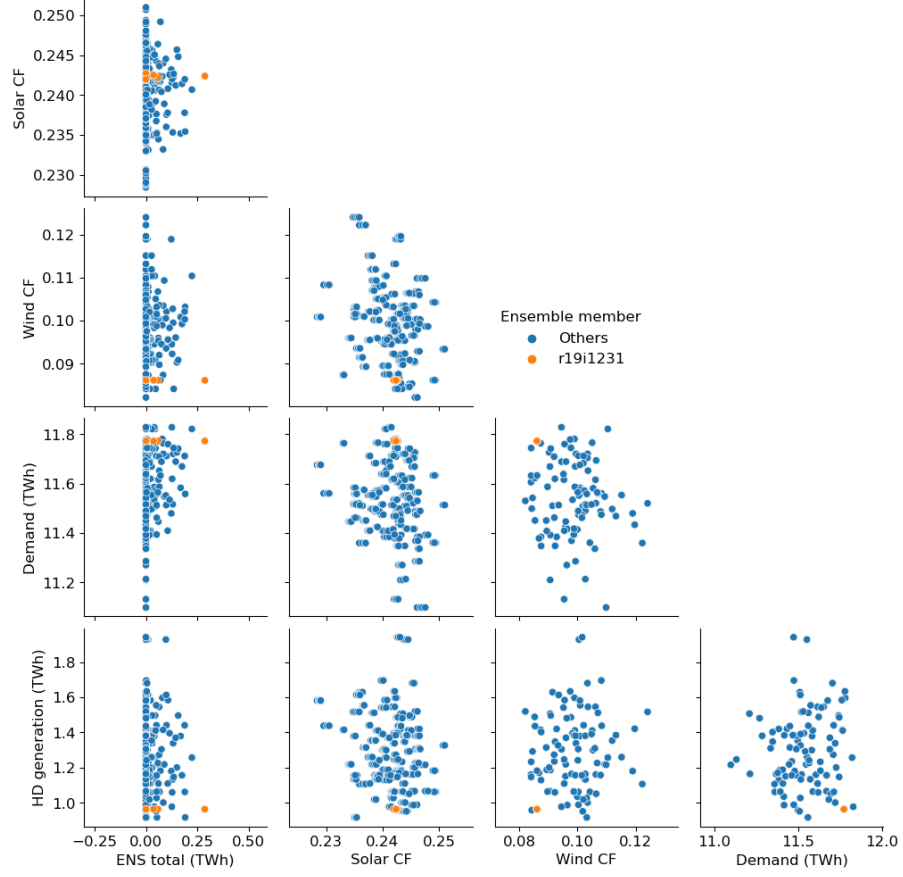


Figure S11: Pair plots of weather-driven energy system variables in the five initial decarbonization pathways. Variables are annual average solar and wind capacity factors, total annual daily demand, total annual daily hydroelectric generation, and total annual energy not served. Data is shown for California (CAMX) only, the largest demand region, for 2040. Yellow dots show outcomes when each pathway is run under the r19i1231p1f2 ensemble member, while blue dots show outcomes while each pathway is run under each of the other 99 ensemble members, thereby illustrating differences between r19i1231p1f2 and other members (high demand, low hydropower, and low wind).

S2 Climate Data

The CESM2 Large Ensemble is designed to capture perturbations of the earth system and discover plausible states of future climates by starting the climate model (CESM2) simulations from different initial conditions. These initial conditions capture different states of the atmosphere and ocean, by sampling specific years of a pre-industrial control run and also another set based on different states of the Atlantic Meridional Overturning Circulation (AMOC) and further perturbing these by varying the atmospheric potential temperature. The 100 ensembles used in this study is the full ensemble available in the LENS2 dataset. The different forcing conditions used for the two groups in the dataset vary in their biomass burning (BMB) protocol, one which uses the CMIP6 forcing (observed remote sensing data for 1997-2014) and other which uses a smoothed version of this BMB protocol with 11-year running means to reduce the variability.

Variables obtained from CESM2-LE and their features are shown in table S1

Variable Long Name	Short Name	Units	Frequency	Bias Correction Method	Usage in This Study
Reference height temperature	TREFHT	K	Daily	Mean bias shifting	Demand forecasting, power plant derating and outages, solar and wind capacity factors
Downwelling solar flux at surface	FSDS	W/m^2	Daily	-	Solar capacity factors
10m wind speed	U10	m/s	Daily	Mean bias shifting	Solar and wind capacity factors
Surface pressure	PS	Pa	Daily	-	Wind capacity factors, power plant derating
Reference height humidity	QREFHT	kg/kg	Daily	-	Wind capacity factors, power plant derating
Total liquid runoff not including correction for land use change	QRUNOFF	mm/s	Month	Mean bias scaling	Hydroelectric generation

Table S1: Information about CESM2-LE variables obtained, processing applied to them, and their usage.

S2.1 Driving Ensemble Parameters

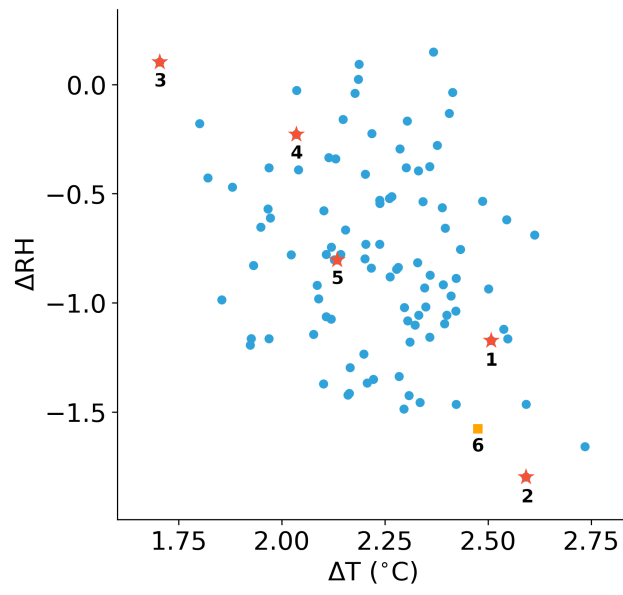


Figure S12: Difference between 2035-2065 and 1985-2015 climatology of surface temperature and relative humidity for the 100 CESM2-LE ensemble members. The stars show ΔT and ΔRH the ensemble members chosen for capacity expansion runs. Refer table S2 for information about the selected ensemble members.

Index	LENS2 member ID	ΔT ($^{\circ}\text{C}$)	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
6	r19i1231p1f2	2.48	-1.57

Table S2: ΔT , ΔRH , and ensemble ID of the members chosen for expansion planning. Index corresponds to star labels in Figure S12.

S2.2 Bias Correction

S2.2.1 Surface Temperature

1. Get ensemble mean temperature mean over geography of interest
2. Compare with mean of ERA5 temperature regridded to the LENS2 grid over same geography
3. Calculate bias correction factor as $\delta_T = \overline{y_f} - \overline{y_{ra}}$
4. Calculate bias corrected temperature as $y_{f,corr} = y_f - \delta_T$

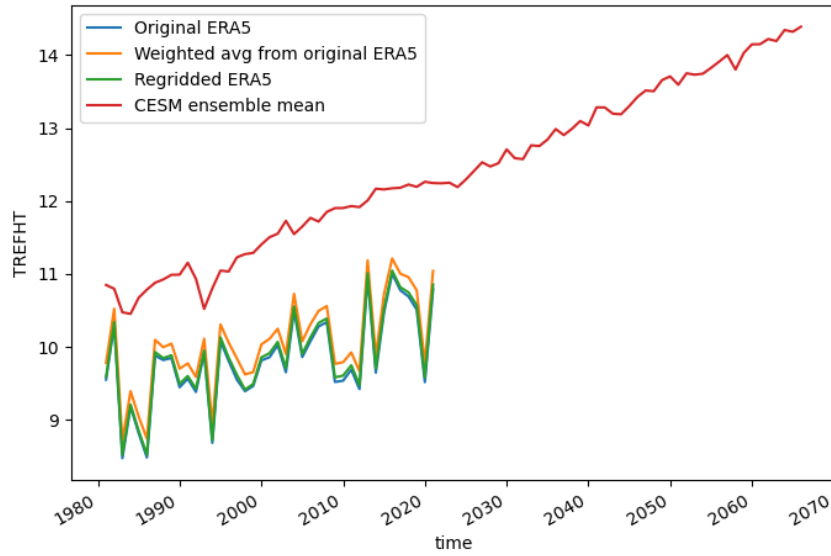


Figure S13: Comparison of LENS2 ensemble mean temperature and ERA5 temperature for different methods of averaging.

S2.3 Capacity factors

We derive solar capacity factors from surface downwelling shortwave flux data for a EFG-Polycrystalline silicon photovoltaic module using the formulation described by Jerez et. al. (Jerez et al., 2015) [See SI section 1.1]. We calculate wind capacity factors from the 10m wind speed data using the formulation described by Karinauskas et. al. (Karinauskas et al., 2018) and the composite 1.5 MW IEC class III turbine from the System Advisor Model (Blair et al., 2018).

965 **S2.3.1 Solar**

966 We derive daily solar capacity factors for a EFG-Polycrystalline silicon photovoltaic
967 module as (Jerez et al., 2015):

$$CF_{pv}^t = P_R^t \frac{FSDS^d}{FSDS_{STC}} \quad (1)$$

968 where $FSDS^d$ represents surface downwelling shortwave flux in air [Wm^{-2}] where the
969 superscript d indexes the day. All the meteorological variables are discrete in time and
970 space (at the dataset resolution), and the index d is dropped hereafter for conciseness.
971 In eq.1, $FSDS_{STC}$ refers to FSDS at standard test conditions and is equal to $1000Wm^{-2}$,
972 and P_R^t is the performance ratio calculated using

$$P_R = 1 + \gamma[T_{cell} - T_{STC}] \quad (2)$$

$$T_{cell} = c_1 + c_2 TREFHT + c_3 FSDS + c_4 SWS \quad (3)$$

973 where T_{cell} is the PV cell temperature, TREFHT is surface air temperature ($2m$ tem-
974 perature and SWS is surface wind speed. In eq.2, $\gamma = -0.005^\circ C^{-1}$ and $T_{STC} = 25^\circ C$.
975 In eq.3, $c_1 = 4.3^\circ C$, $c_2 = 0.943$, $c_3 = 0.028^\circ C m^2 W^{-1}$, and $c_4 = -1.528^\circ C sm^{-1}$
976 (Tamizhmani et al., 2003).

977 **S2.3.2 Wind**

978 We calculate wind capacity factors using the formulation described in (Karnauskas
979 et al., 2018) for the composite 1.5 MW IEC class III turbine with power curves from the
980 System Advisor Model (SAM) (Blair et al., 2018) as:

$$CF_{wind}^d = p(W_{100}^d) \quad (4)$$

981 where p is a function describing the power curve and W_{100}^d is the daily corrected 100m
982 wind speed. The correction accounts for air density and humidity related effects on the
983 wind turbine performance and is carried out as:

$$W'_{100} = W_{10} \left(\frac{100m}{10m} \right)^{1/7} \quad (5)$$

$$W_{100} = W'_{100} \left(\frac{\rho_m}{1.225} \right)^{1/3} \quad (6)$$

$$\rho_m = \rho_d \left(\frac{1 + QREFHT}{1 + 1.609 \times HUSS} \right) \quad (7)$$

$$\rho_d = \frac{PS}{R \times (T + 273.15)} \quad (8)$$

Eqs.5 and 6 scales the 10m wind speed to 100m and correct for air density as this affects the force exerted on the turbine blades, where ρ_m is the humidity corrected air density, which is in turn derived from the surface specific humidity ($HUSS$) as shown in eq.7. ρ_d is the dry air density which is derived using the ideal gas law from surface pressure [units-Pa](PS) and surface temperature (T) as shown in eq.8, where $R = 287.058 J kg^{-1} K^{-1}$ is the gas constant.

We estimate wind generation for all locations across WECC assuming a class-III wind turbine. The power curve from SAM is provided as the power output at discrete wind speeds (figure S14), and we convert this into a continuous function through linear interpolation. We include the discrete power curve in this SI.

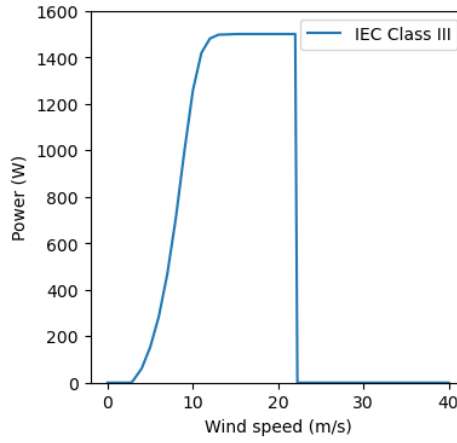


Figure S14: Power curve for 1.5 MW IEC class III turbine

S2.4 Hydroelectricity generation

We obtain monthly hydroelectric generation forecasts using a linear regression model which predicts hydro electric generation as a function of runoff. We train the regression against cleaned plant level hydroelectric generation from the RectifHyd dataset (Turner, Voisin, & Nelson, 2022) and river run-off from the ERA5-land dataset. To predict the hydro generation for each ensemble member we use the runoff data from the LENS2 dataset. Owing to the coarse resolution of the LENS2 data, and computational costs to obtain river run and reservoir flows, we build our regression models for individual “drought regions” (Figures S15, S16, and S17). These drought regions represent eight hydropower

climatic regions for the western US, and determined using clustering techniques based on similarity of climatic conditions and reservoir characteristics (Turner, Voisin, Nelson, & Tidwell, 2022).

We carry out the hydroelectric generation forecasting with the following steps:

1. ERA5 representation of runoff is daily accumulations at 00 hours in m/day and averaged over month, cesm is daily mean at mm/day averaged over month, so we reconcile these to the same units.
2. There is a bias between LENS2 and ERA5-Land datasets, so we bias correct LENS2 data ensemble mean to match reanalysis data for the period 1980-2020 using a scaling factor. Figure S18 shows the bias correction factors for each drought region. The range in the figure represents the bias correction factors if we corrected each ensemble member individually rather than correcting the ensemble mean.
3. We then train our regression models to predict annual generation (for a hydrological year), using the observed hydro generation data and ERA5 surface run off. We predict annual generation based on LENS2 data and use the monthly shapes in figure S19 to get monthly generation.
4. Figures S20 and S21 show predicted hydroelectric generation from all ensembles at the drought regional level and from 1 ensemble for the WECC subregions respectively.

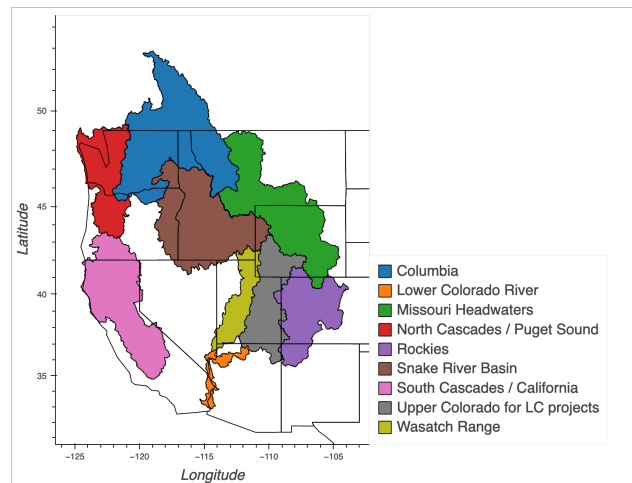


Figure S15: Drought regions used in the RectifHyd dataset

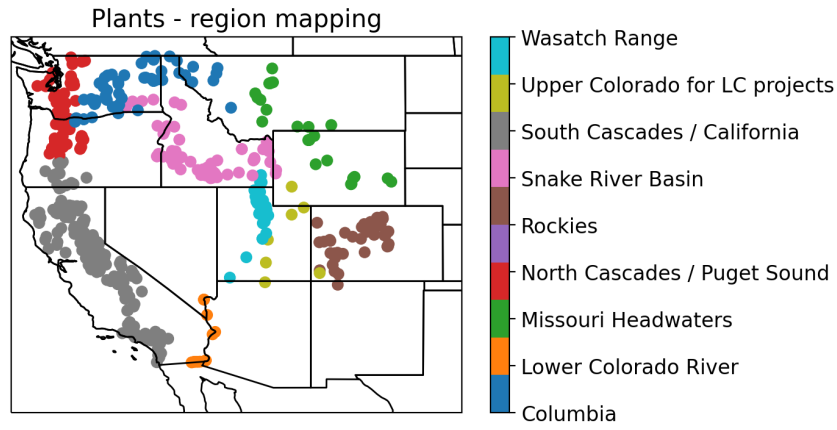


Figure S16: Mapping of hydropower plants in WECC to the drought regions

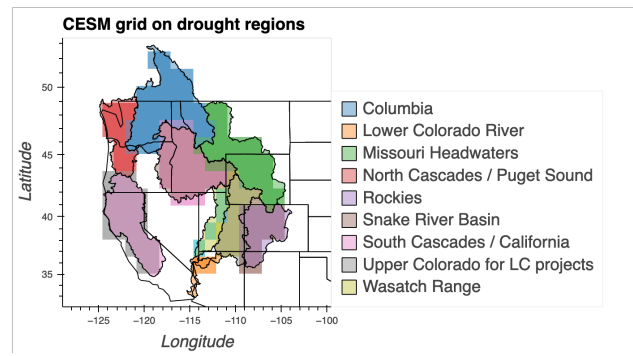


Figure S17: Mapping of CESM grid cells to the drought regions

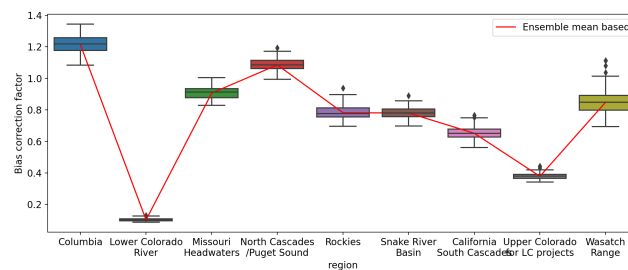


Figure S18: Bias correction factors for the drought regions.

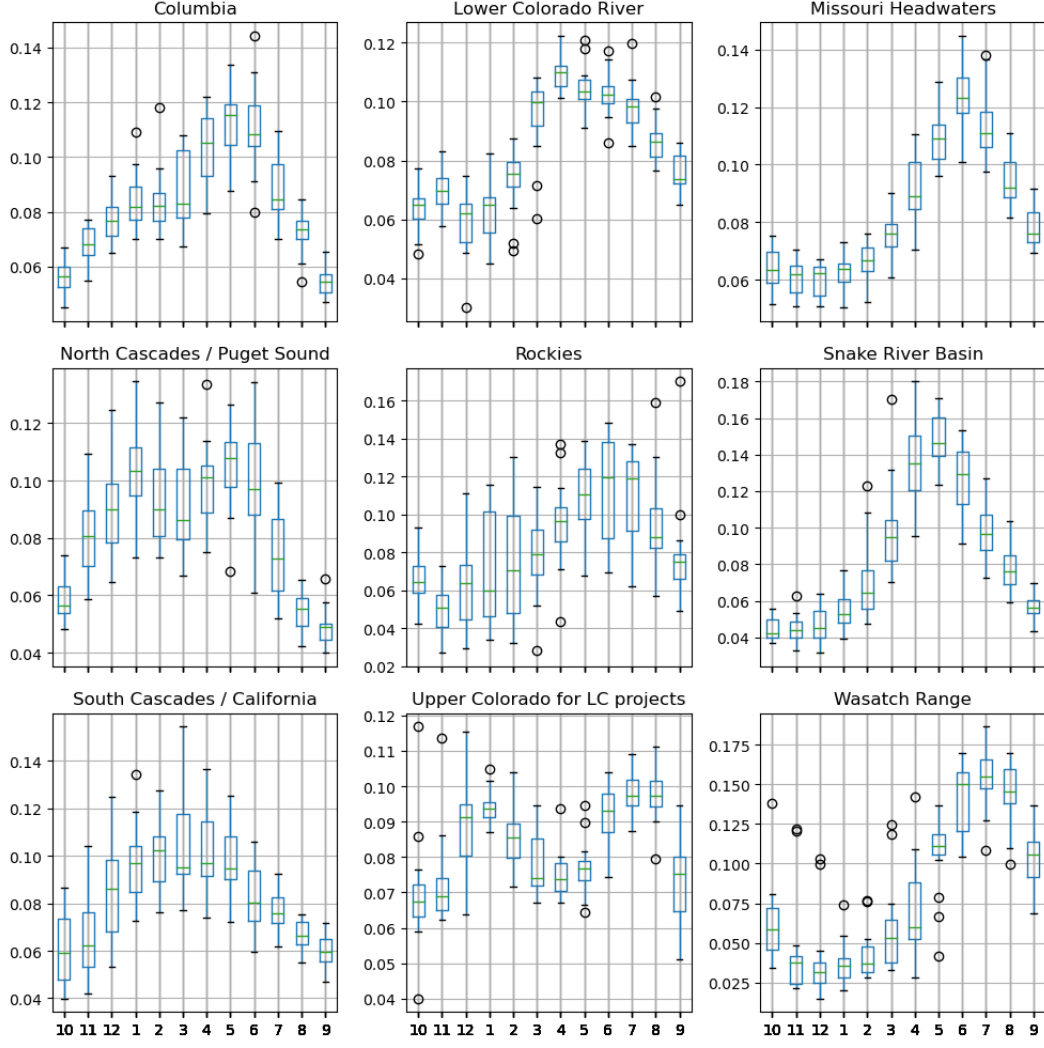


Figure S19: Annual to monthly disaggregation shapes, where y-axis shows the fraction of total annual generation in each month, and the boxplot shows the variability on all the years available in the RectifHyd dataset.

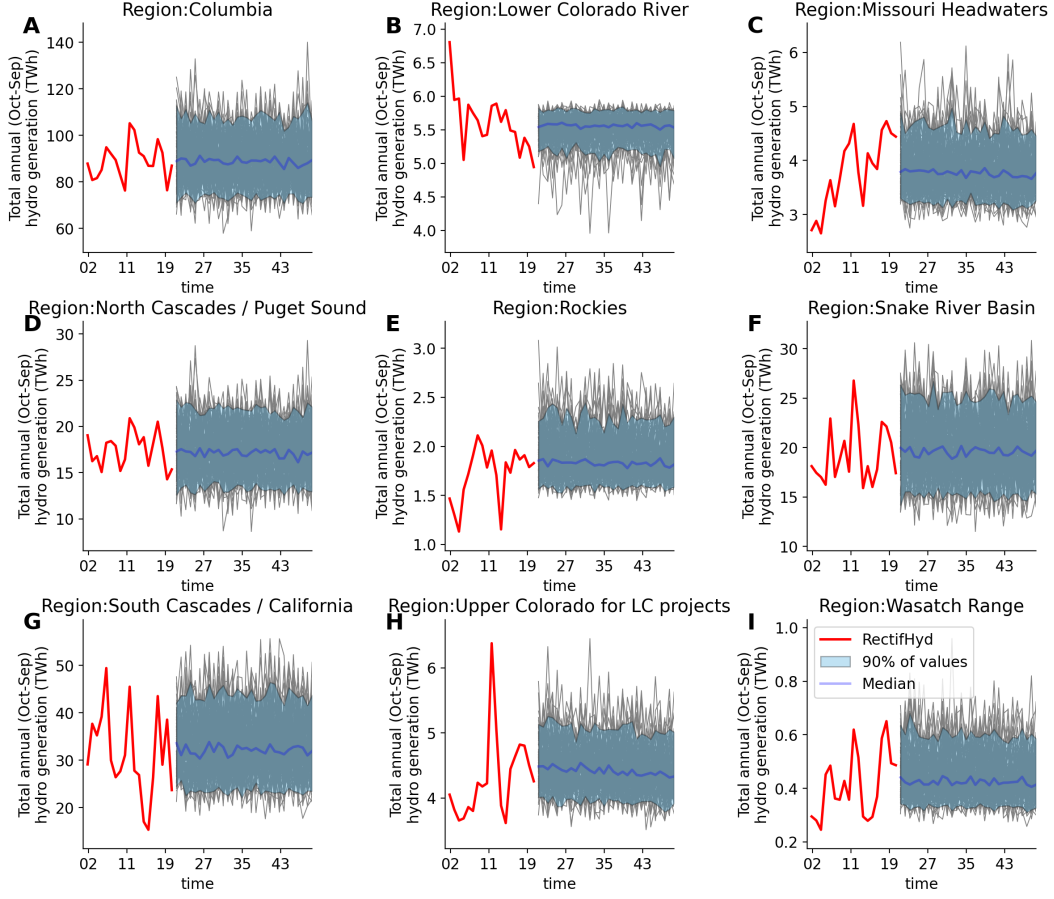


Figure S20: Comparison of annual hydroelectric generation from all ensembles against observations showing that the range of our predicted annual generation values across ensembles is generally representative of mean and range of historic values, especially for large systems like Southern Cascades, Columbia, Northern Cascades, and Snake River. Here x-axis is the year, that is 43 is October 2042 - September 2043.

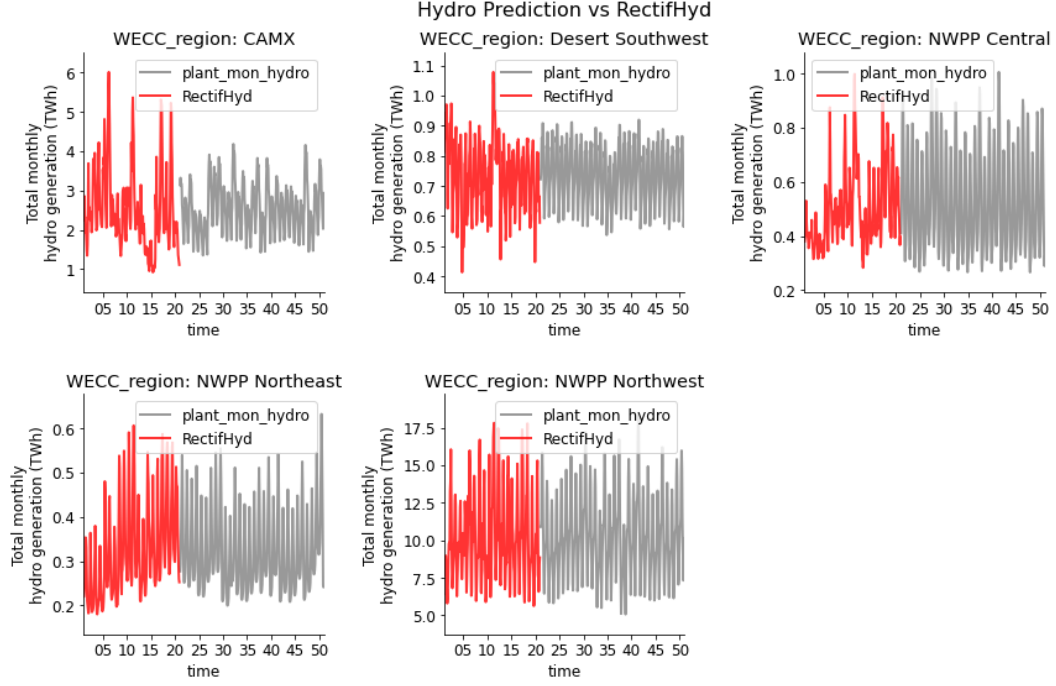


Figure S21: WECC subregional hydroelectric generation for the *r4i1061p1f1* ensemble.

Here x-axis is month (but since we show a large time period, the axis labels correspond to the year).

S3 Demand Forecasting

We derive daily subregional demand for each ensemble member using a piecewise linear regression (PLR) model (Ralston Fonseca et al., 2019). The model predicts daily demand from subregional averaged daily surface temperature. We train the model with daily demand data, which is obtained by processing observed demand (Ruggles et al., 2020), and observed daily temperatures from ERA5. In the regression formulation we include fixed effects based on day of the week and the season. We obtain temperature bins to apply the piecewise model by splitting the subregional temperatures into 6 bins containing same number of datapoints. Because the subregions experience different temperature, we have different bins for each subregion.

S3.1 Regional Demand for Electricity

The sub-regional loads are constructed by aggregating loads in smaller balancing authorities located within their boundaries [Table S3].

Sub-region	Balancing Authorities aggregated to find demand
CAMX	CISO, BANC, TIDC, LDWP
Desert Southwest	IID, AZPS, SRP, EPE, PNM, TEPC, WALC
NWPP Central	NEVP, PACE, IPCO, PSCO
NWPP NE	WACM, NWMT, WAUW, PACE
NWPP NW	PSEI, DOPD, CHPD, AVA, TPWR, GCPD, BPAT, PGE, PACW, SCL

Table S3: Sub-region – balancing authority mapping to obtain aggregate demand

Subregion	Temperature Bins (°C)					
	Segment 1	Segment 2	Segment 3	Segment 4	Segment 5	Segment 6
CAMX	[0.83,8.44)	[8.44,11.72)	[11.72,15.34)	[15.34,19.52)	[19.52,24.63)	[24.63,29.82)
Desert Southwest	[-5.46,6.18)	[6.18,10.78)	[10.78,15.59)	[15.59,20.82)	[20.82,25.17)	[25.17,30.89)
NWPP Central	[-16.23,-0.94)	[-0.94,4.31)	[4.31,9.14)	[9.14,15.33)	[15.33,21.85)	[21.85,26.88)
NWPP NE	[-23.87,-5.27)	[-5.27,0.47)	[0.47,5.63)	[5.63,11.61)	[11.61,17.83)	[17.83,25.58)
NWPP NW	[-13.73,0.10)	[0.10,4.05)	[4.05,7.68)	[7.68,12.80)	[12.80,17.95)	[17.95,25.92)

Table S4: Temperature bins for piecewise linear regression by subregion.

Subregion	Coefficient corresponding to					
	Segment 1	Segment 2	Segment 3	Segment 4	Segment 5	Segment 6
CAMX	-73.38	-99.82	305.46	513.98	1038.17	1731.93
Desert Southwest	-169.99	-0.18	170.67	439.61	624.10	497.94
NWPP Central	-115.00	-158.59	-88.00	164.17	397.05	523.58
NWPP NE	-36.83	-51.61	-63.73	-6.91	97.34	154.42
NWPP NW	-406.10	-448.34	-460.85	-163.03	179.54	352.19

Table S5: Coefficients of corresponding segments from table S4

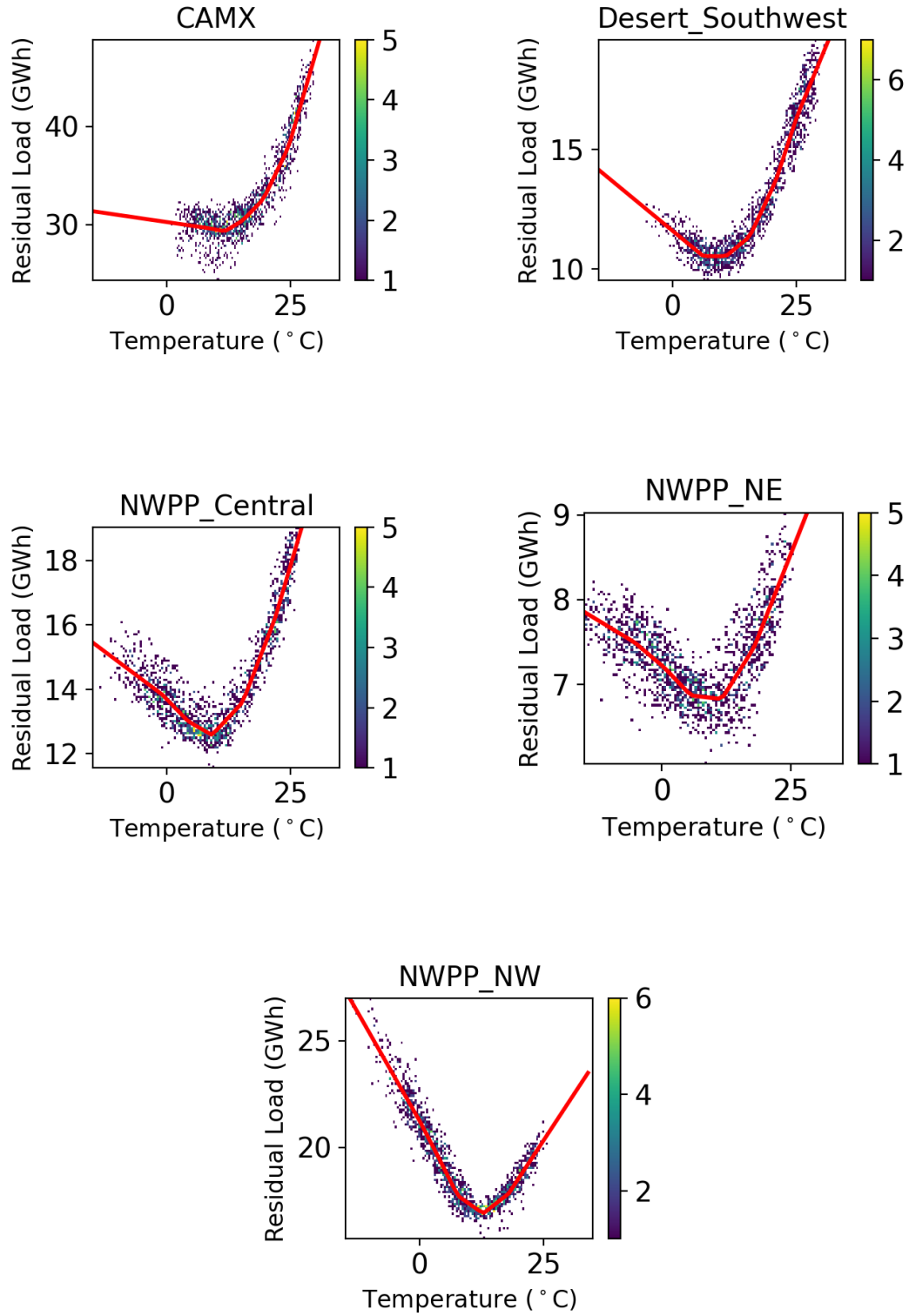


Figure S22: Two dimensional histogram of residual load vs air temperature, where the red line shows the fitted piece-wise regression model and colors show frequency of occurrence of each residual load vs temperature pair. Here, residual load isolates the temperature-dependent portion of load

S4 Capacity Deratings and Temperature-Dependent Forced Outage Rates of Fossil-Based Thermal Power Plants

Fossil-based thermal power plants are vulnerable to capacity deratings, or reductions in available generating capacity. We estimate deratings using existing bottom-up relationships for steam turbine and combined cycle (CC) plants with recirculating or dry cooling and for combustion turbines. Deratings for plants with once through cooling are driven by water intake conditions (e.g., river temperatures) and regulations, so requires detailed hydrological modeling outside of our analytic scope. We approximate deratings of coal and CC facilities with carbon capture and sequestration (CCS) to be the same as coal and CC facilities without CCS. Deratings are calculated following the methods following Craig et al. (2020), which sources a bottom-up derating estimate for combustion turbines from Bartos and Chester (2015) and a statistical model of deratings at coal and gas STs and CCs from Loew et al. (2018). In these relationships, CT deratings are a function of surface air temperatures; STs and CCs with recirculating cooling (RC) are a function of surface air temperatures and relative humidity; and STs and CCs with dry cooling (DC) are a function of surface air temperatures and surface air pressure. RC and DC facilities have varying designs, which in turn have varying vulnerabilities to thermal deratings. Data on RC and DC designs is not publicly available, so we assume RC and DC designs that are moderately resilient against deratings. Specifically, we assume a RC design of inlet and outlet cooling water temperatures of 75 and 95 degrees F, respectively, and a DC design with an initial temperature difference of 45 degrees F. We obtain cooling types by power plant from EIA Form 860 (EIA, 2022).

We calculate temperature-dependent forced outage rates for thermal power plants using the best available plant-type-specific relationships from existing literature (Murphy et al., 2019).

Table S6: Temperature dependent forced outage rates of different generators from Murphy et al. (2019).

Closest temperature value [$^{\circ}C$]	-15	-10	-5	0	5	10	15	20	25	30	35
Nuclear	1.9 %	1.8 %	1.7 %	1.8 %	1.9 %	2.1 %	2.7 %	3.1 %	3.9 %	6.6 %	12.4 %
Combined cycle gas	14.9 %	8.1 %	4.8 %	3.3 %	2.7 %	2.5 %	2.8 %	3.5 %	3.5 %	4.1 %	7.2 %
Simple cycle gas	19.9 %	9.9 %	5.1 %	3.1 %	2.4 %	2.2 %	2.4 %	2.7 %	3.1 %	3.9 %	6.6 %
Steam turbine coal	13.3 %	11.2 %	9.9 %	9.1 %	8.6 %	8.3 %	8.4 %	8.6 %	9.4 %	11.4 %	14. %
Hydro	7 %	4.3 %	3.2 %	2.7 %	2.6 %	2.6 %	2.7 %	2.7 %	2.5 %	2.9 %	8.2 %
Solar, wind, storage, other	5 %	5 %	5 %	5 %	5 %	5 %	5 %	5 %	5 %	5 %	5 %

S5 Capacity Expansion Model

The capacity expansion (CE) model optimizes new capacity investments, operations of new and existing units, and inter-regional electricity transfers by minimizing total system costs subject to system and unit-level constraints. Total system costs equal the sum of the cost of electricity generation of existing and new units and the cost of new capacity investments. Electricity generation costs equal the sum of fixed operations and maintenance (O&M) costs and variable electricity generation costs, which include fuel costs and variable O&M costs. The model runs from 2023 to 2040 in 2-year time steps. In each model run, the CE model can build natural gas combined cycle (NGCC), wind, and solar generators, and can build coal or NGCC with carbon capture and sequestration (CCS) beginning in 2031 given the current immature state of the technology. We obtain overnight capital costs and fixed and variable operation and maintenance (O&M) costs for each time step from NREL's Annual Technology Baseline (ATB) moderate technology development scenario (Akar et al., 2020).

The CEM model divides WECC into five regions; inter-regional transmission and capacity investments are optimized between regions, and supply and demand are balanced within each region (accounting for imports and exports).

To reflect ongoing scale up of wind and solar investment potential, we include a WECC-wide limit on wind and solar investments in each time step. Annual limits begin in the first model run (2023-2024) at 5.2 and 6.8 GW for wind and solar, respectively, or double the maximum annual capacity additions in recent years (2020-2022) since our model runs in 2-year time steps. Maximum potential wind and solar investments grow through 2040 at a compounding annual growth rate of 0.3. In addition to WECC-wide investment limits on wind and solar, we capture local limits on capacity investments following methods outlined by Wu et al. (Wu et al., 2023). In general, we exclude developable area on the basis of environmental, techno-economic, land use, and legal criteria. Exclusions include Bureau of Land Management (BLM) exclusions; United States Geologic Service protected areas; airports; lakes; mines; military areas; census urban zones; flood zones; high slopes; and high population densities. After accounting for exclusions, we sum available area for wind or solar deployment by CESM2 grid cell, convert area to installed capacity using wind and solar densities of 0.9 and 5.7 W per square meter (Miller & Keith, 2018), respectively, and optimize wind and solar investments at the grid cell level.

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S5.1 Functional Forms

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S5.1.1 Parameters and Variables

Parameter	Definition	Unit
P_i^{MAX}	Maximum power rating of existing unit i	MW
P_c^{MAX}	Maximum power rating of new unit c	MW
P_l^{MAX}	Maximum transmission capacity of line l	MW
FOM_c	Fixed O&M cost of new unit c	\$/MW
OCC_c	Overnight capital cost of new unit c	\$/MW
OCC_l	Overnight capital cost of transmission expansion along line l	\$/MW
CRF_c	Capital recovery factor of new unit c	
CRF_l	Capital recovery factor of new transmission line l	
OC_c	Operational cost of new unit c	\$/MWh
VOM_c	Variable O&M cost of new unit c	\$/MWh
VOM_i	Variable O&M cost of existing unit i	\$/MWh
OC_i	Operational cost of existing unit i	\$/MWh
OC_c	Operational cost of new unit c	\$/MWh
FC_c	Fuel cost of new unit c	\$/MMBtu
FC_i	Fuel cost of existing unit i	\$/MMBtu
HR_c	Heat rate of new unit c	MMBtu/MWh
HR_i	Heat rate of existing unit i	MMBtu/MWh
$ER_i^{CO_2}$	CO ₂ emissions rate of existing unit i	ton/MMBtu
$ER_c^{CO_2}$	CO ₂ emissions rate of new unit c	ton/MMBtu
R	Discount rate = 0.07 (Craig, Jaramillo, & Hodge, 2018)	–
LT_c	Life time of new units c	Years
$N_{c_r}^{MAX}$	Maximum capacity of new wind or solar units c built	MW
$P_{c_r}^{WECC,MAX}$	Maximum number of total renewable capacity c_r built WECC-wide	MW
$D_{z,t}$	Total load (or electricity demand) in region z at time t	MWh
D_t	Total load (or electricity demand) across regions at time t	MWh

Parameter	Definition	Unit
$P_{t,z}^{MAX,WIND}$	Maximum aggregate wind profile in region z at time t	MW
$P_{t,z}^{MAX,SOLAR}$	Maximum aggregate solar profile in region z at time t	MW
$H_{b,z}$	Maximum hydropower generation in region z and month b	MWh
$FOR_{i,t}$	Forced outage rate of existing unit i at time t	–
$DR_{i_{th},t}$	Capacity derate of existing thermal CT, CC, or coal plants i_{th} at time t	–
$DR_{c_{th},t}$	Capacity derate of new thermal CC or coal plants c_{th} at time t	–
FOR_t^{RE}	Forced outage rate of existing wind and solar units at time t	–
$FOR_{c,t}$	Forced outage rate of new unit c at time t	–
$E_{CO_2}^{MAX}$	WECC-wide carbon dioxide emissions cap	tons
$CF_{c_r,t}$	Capacity factor of new renewable unit c_r at time t	–
RL_i	Maximum ramp rate of existing unit i	MW
RL_c	Maximum ramp rate of new unit c	MW
ν	Transmission losses per unit of electricity transferred between regions	%

Table S7: List of Parameters (Continued)

Set	Definition	Index	Note
$\mathbb{C}$	Set of potential new units	c	–
$\mathbb{C}_z$	Set of potential new units in region z	c_z	$\mathbb{C}_z \in \mathbb{C}$
$\mathbb{C}_r$	Set of potential new renewable units	c_r	$\mathbb{C}_r \in \mathbb{C}$
$\mathbb{C}_{th}$	Set of potential new coal or NGCC thermal units	c_{th}	$\mathbb{C}_{th} \in \mathbb{C}$
$\mathbb{I}$	Set of existing units	i	–
$\mathbb{I}_z$	Set of existing units in region z	i_z	$\mathbb{I}_z \in \mathbb{I}$
$\mathbb{I}_r$	Set of existing renewable units	i_r	$\mathbb{I}_r \in \mathbb{I}$
$\mathbb{I}_{th}$	Set of existing CT, CC, or coal thermal units	i_{th}	$\mathbb{I}_{th} \in \mathbb{I}$
$\mathbb{I}_w$	Set of existing wind units	i_w	$\mathbb{I}_w \in \mathbb{I}$
$\mathbb{I}_{wz}$	Set of existing wind units in region z	i_{wz}	$\mathbb{I}_{wz} \in \mathbb{I}_w$
$\mathbb{I}_o$	Set of existing solar units	i_o	$\mathbb{I}_o \in \mathbb{I}$
$\mathbb{I}_{oz}$	Set of existing solar units in region z	i_{oz}	$\mathbb{I}_{oz} \in \mathbb{I}_o$
$\mathbb{L}$	Set of transmission lines	l	–
$\mathbb{L}_z^{OUT}$	Set of transmission lines flowing out of region z	l_z^{OUT}	$\mathbb{L}_z^{OUT} \in \mathbb{L}$
$\mathbb{L}_z^{IN}$	Set of transmission lines flowing into region z	l_z^{IN}	$\mathbb{L}_z^{IN} \in \mathbb{L}$
$\mathbb{B}$	Set of months	b	–
$\mathbb{T}$	Set of days	t	–
$\mathbb{T}_p$	Set of peak demand day	t_p	$\mathbb{T}_p \in \mathbb{T}$
$\mathbb{Z}$	Set of regions in WECC	z	–

Table S8: List of Sets

Variable	Definition	Unit
n_c	Number of new units built of type c	
n_l	Total new transmission line capacity investments in line l	MW
$p_{i,t}$	Electricity generation from existing unit i at time t	MWh
$p_{c,t}$	Electricity generation from new unit c at time t	MWh
$f_{l,t}$	Total electricity flow in line l at time t	MWh

Table S9: List of Variables

S5.2 Objective Function

The CE model's objective function minimizes total annual fixed plus variable costs, where fixed costs capture investment costs in new transmission and electricity generators, and variable costs capture operational costs of new and existing generators:

$$\begin{aligned}
 TC^{CE} = & \left[\sum_c n_c \times P_c^{MAX} \times (FOM_c + OCC_c \times CRF_c) \right] \\
 & + \left[\sum_l n_l \times OCC_l \times CRF_l \right] + \left[\sum_t \left(\sum_c p_{c,t} \times OC_c + \sum_i p_{i,t} \times OC_i \right) \right], \\
 & \forall i \in \mathbb{I}, c \in \mathbb{C}, l \in \mathbb{L}, t \in \mathbb{T}
 \end{aligned} \tag{9}$$

where c indexes potential new units; t indexes time intervals (days); i indexes existing units; l indexes potential new transmission lines; n_c is number of new unit investments, which is a continuous positive variable; n_l is total new transmission line capacity investments in line l (MW); P^{MAX} is maximum capacity of unit (MW); FOM is fixed operation and maintenance (O&M) costs of units (\$/MW/year); OCC is overnight capital cost of new investments (\$/MW); CRF is capital recovery factor; p_c is electricity generation from new unit c (MWh); p_i is electricity generation from existing unit i (MWh); and OC is operational costs of new or existing units (\$/MWh). OC is defined for new

1106 and existing generators as:

$$OC_i = VOM_i + HR_i \times FC_i \quad \forall i \in \mathbb{I}, \quad (10a)$$

$$OC_c = VOM_c + HR_c \times FC_c \quad \forall c \in \mathbb{C} \quad (10b)$$

1107 where VOM is variable O&M costs (\$/MWh), HR is heat rate (MMBtu/MWh),
1108 and FC is fuel cost (\$/MMBtu). CRF_c is defined as:

$$CRF_c = \frac{R}{1 - \frac{1}{(1+R)^{LT_c}}} \quad \forall c \in \mathbb{C}, \quad (11)$$

1109 where R is discount rate and LT is plant lifetime (years).

1110 S5.3 System-level Constraints

1111 The CE model requires total adjusted capacity to meet peak annual demand on
1112 a WECC-wide basis:

$$\begin{aligned} D_t \leq & \sum_{c_{th}} P_{c_{th}}^{MAX} \times (1 - FOR_{c_{th},t}) \times (1 - DR_{c_{th},t}) \times n_{c_{th}} \\ & + \sum_{c_r} P_{c_r}^{MAX} \times (1 - FOR_{c_r,t}) \times n_{c_r} \times CF_{c_r,t} \\ & + \sum_i (1 - FOR_{i,t}) \times P_i^{MAX} \\ & + \sum_{i_{th}} (1 - FOR_{i_{th},t}) \times (1 - DR_{i_{th},t}) \times P_{i_{th}}^{MAX} \\ & + \sum_z \left(P_{z,t}^{MAX,SOLAR} + P_{z,t}^{MAX,WIND} \right) \times (1 - FOR_t^{RE}), \end{aligned} \quad (12)$$

$$\forall t \in \mathbb{T}_p, c_{th} \in \mathbb{C}_{th}, c_r \in \mathbb{C}_r, i \in \mathbb{I} - \mathbb{I}_W - \mathbb{I}_O - \mathbb{I}_{TH}, i_{th} \in \mathbb{I}_{TH}, z \in \mathbb{Z}$$

1113 where c_{th} and c_r index new thermal and renewable plant types, respectively; i_w and
1114 i_o index existing wind and solar generators, respectively; z indexes regions; FOR is forced
1115 outage rate; CF is capacity factor; $P^{MAX,SOLAR}$ is maximum regional generation by
1116 existing solar generators (MWh); $P^{MAX,WIND}$ is maximum regional generation by ex-
1117 isting wind generators (MWh); and T_p indicates the annual peak demand day. Adjusted
1118 capacity here accounts for temperature-dependent forced outage rates of generators [Ta-
1119 ble S6] and daily capacity factors for wind and solar facilities.

1120 The CE model also requires supply balance demand at each time step:

$$D_{z,t} + \sum_{l_z^{OUT} \in \mathbb{L}_z^{OUT}} f_{l_z^{OUT},t} \leq \sum_{i_z \in \mathbb{I}_z} p_{i_z,t} + \sum_{c_z \in \mathbb{C}_z} p_{c_z,t} + \sum_{l_z^{IN} \in \mathbb{L}_z^{IN}} f_{l_z^{IN},t} \times \nu, \quad \forall z \in \mathbb{Z}, t \in \mathbb{T}, \quad (13)$$

1121 where z indexes zones, l indexes transmission lines, i_z indexes existing units in re-
 1122 gion z , c_z indexes new units in region z , l_z^{IN} indexes lines flowing into region z , l_z^{OUT} in-
 1123 dexes transmission lines flowing out of region z , ν indicates losses for each unit of elec-
 1124 tricity imported into a region (assumed to be 5%, and only applied to inflows to avoid
 1125 double counting of losses), and f is electricity flows along transmission lines. Transmis-
 1126 sion line sets L_z^{OUT} and L_z^{IN} are subsets of the full transmission line set L . Mapping of
 1127 lines between sets ensures imports and exports are accounted for properly in each region's
 1128 power balance. Transmission flows are only positive, and lines allow for flows in a sin-
 1129 gle direction, such that two lines connect CAMx and DSW, one for flows from CAMx
 1130 to DSW and another for flows from DSW to CAMx.

1131 The total electricity flow through a transmission line ($f_{l,t}$) cannot exceed the line's
 1132 initial transmission capacity (P_l^{MAX}) plus new capacity investments (n_l):

$$0 \leq f_{l,t} \leq P_l^{MAX} + n_l, \quad \forall l \in \mathbb{L}, t \in \mathbb{T}, \quad (14)$$

1133 where l indexes transmission lines, and $f_{l,t}$ is total electricity flow in line l at time t (MWh).

1134 To examine power systems that meet a decarbonization target, we enforce a CO₂
 1135 emission cap ($E_{CO_2}^{MAX}$ on WECC-wide emissions:

$$E_{CO_2}^{MAX} \geq \left[\sum_t \left(\sum_i p_{i,t} \times HR_i \times ER_i^{CO_2} + \sum_c p_{c,t} \times HR_c \times ER_c^{CO_2} \right) \right], \quad \forall t \in \mathbb{T}, \forall i \in \mathbb{I}, \forall c \in \mathbb{C} \quad (15)$$

1136 where ER^{CO_2} is CO₂ emission rate (ton/MMBtu). This cap declines linearly over time
 1137 from 2022 through 2040 to reach a reduction of 60% of 2022 emissions by 2040.

1138 As detailed above, we enforce a WECC-wide cap on wind and solar investments
 1139 ($P_{c_r}^{WECC,MAX}$) (MW) to reflect scaling up of both industries:

$$\sum_{c_r} n_{c_r} \times P_{c_r}^{MAX} \leq P_{c_r}^{WECC,MAX}, \quad \forall c_r \in \mathbb{C}_r \quad (16)$$

1140 where n_{c_r} equals investment in new wind or solar plants. This cap increases over years,
 1141 as described in the Methods, but for a single CE run that occurs for a single year, the
 1142 cap is treated as a fixed value.

S5.4 Unit-level Constraints

S5.4.1 Investment constraints

As explained above, the CE model places an upper bound on wind and solar investments by grid cell based on the area of each grid cell; restrictions on development based on technoeconomic, legal, environmental, and land-use criteria; and the energy density of wind and solar:

$$0 \leq n_{c_r} \times P_{c_r}^{MAX} \leq N_{c_r}^{MAX}, \quad \forall c_r \in \mathbb{C}_r \quad (17)$$

where n_{c_r} equals investment in new wind or solar plants and $N_{c_r}^{MAX}$ equals the maximum investment in new wind or solar plants by grid cell. Existing wind and solar capacities are subtracted from the grid cell's maximum capacity in calculating $N_{c_r}^{MAX}$.

S5.4.2 Generation constraints

For existing generators, electricity generation is limited by the generators' capacities:

$$0 \leq p_{i,t} \leq P_i^{MAX}, \quad \forall t \in \mathbb{T}, i \in \mathbb{I} \quad (18)$$

Thermal plants are vulnerable to deratings at certain ambient air temperatures. We account for deratings of combustion turbines, NGCCs, and coal-fired power plants across space and time (Section SI.S4) and limit their daily generation to their derated capacity as follows:

$$p_{i_{th},t} \leq DR_{i_{th},t} \times P_{i_{th}}^{MAX}, \quad \forall t \in \mathbb{T}, i_{th} \in \mathbb{I}_{th} \quad (19a)$$

$$p_{c_{th},t} \leq n_{c_{th}} \times DR_{c_{th},t} \times P_{c_{th}}^{MAX}, \quad \forall t \in \mathbb{T}, c_{th} \in \mathbb{C}_{th} \quad (19b)$$

Combined electricity generation by existing wind and solar generators is limited to aggregate wind and solar generation profiles:

$$\sum_{i_{w_z} \in \mathbb{I}_{w_z}} p_{i_{w_z},t} \leq P_{z,t}^{MAX,WIND}, \quad \forall t \in \mathbb{T}, z \in \mathbb{Z}, \quad (20a)$$

$$\sum_{i_{o_z} \in \mathbb{I}_{o_z}} p_{i_{o_z},t} \leq P_{z,t}^{MAX,SOLAR}, \quad \forall t \in \mathbb{T}, z \in \mathbb{Z}, \quad (20b)$$

New generators' electricity generation cannot exceed their new capacity investments:

$$0 \leq p_{c,t} \leq n_c \times P_c^{MAX}, \quad \forall t \in \mathbb{T}, c \in \mathbb{C} \quad (21)$$

Electricity generation by new renewable generators is also constrained by site-specific capacity factor timeseries:

$$p_{c_r,t} \leq n_{c_r} \times P_{c_r}^{MAX} \times CF_{c_r,t}, \quad \forall t \in \mathbb{T}, c_r \in \mathbb{C}_r \quad (22)$$

Hydropower generation is constrained based on observed data for each of our weather years. Since we ignore transmission constraints within each of our five regions, we aggregate hydropower capacity by region, then limit total hydropower generation by month (or time block):

$$\sum_{t_b \in T_b, i_{h_z} \in I_{h_z}} p_{i_{h_z}, t_b} \leq H_{b,z}, \forall z \in \mathbb{Z}, b \in \mathbb{B} \quad (23)$$

where i_{h_z} indexes all hydropower units in region z and $H_{b,z}$ equals maximum total hydropower generation in month b and region z [??].

The CE model places an upper bound on upwards changes in electricity generation from one time period to the next, i.e. in upward ramps, for new and existing units:

$$p_{i,t_b} - p_{i,t_b-1} \leq RL_i, \quad \forall t_b > 1, i \in \mathbb{I} \quad (24a)$$

$$p_{c,t_b} - p_{c,t_b-1} \leq n_c \times P_c^{MAX} \times RL_c \quad \forall t_b > 1, c \in \mathbb{C} \quad (24b)$$

where RL equals the ramp limit. We only constrain upwards ramps for two reasons: (1) downward ramps can be more easily achieved through curtailment of renewables than upwards ramps and (2) for computational tractability.

S5.5 Data

In this section, we discuss the data and intermediate steps to calculate the parameters that are used in the model.

S5.5.1 Regional Demand for Electricity

The sub-regional loads are constructed by aggregating loads in smaller balancing authorities located within their boundaries per table S3.

S5.5.2 Generator Fleet

S5.5.2.1 Initial Generator Fleet To construct our 2022 initial representative existing generator fleet, we begin with unit-level data on active existing units from *The National Electric Energy Data System* (NEEDS) dataset version 6 (updated in February

Sub-region	CC gas	OC gas	Hydro	Nuclear	Coal	Solar	Wind	Other
CAMX	20641	10825	10147	0	17	10644	5764	4010
Desert Southwest	11256	4855	3840	3937	5333	2303	1488	363
NWPP Central	10486	5053	954	0	6693	3128	3636	1045
NWPP NE	94	465	3493	0	6562	40	2906	23
NWPP NW	6619	1669	32091	1180	0	356	6568	557

Table S10: Initial generator fleet capacity of each generator type (in MW) across the sub-regions. CC indicates combined cycle; OC open cycle; and coal plants are steam turbine plants.

2023) (EPA, 2023). We merge the NEEDS dataset with the EIA860 dataset to get power plant latitudes and longitudes using the ORIS Plant Code (EIA, 2022), and add carbon dioxide (CO₂) emission rates from the the U.S. Energy Information Administration (EIA)'s *Carbon Dioxide Emissions Coefficients* (EIA, 2020.), fuel prices from EIA's *Annual Energy Outlook 2023, Table 3. Energy Prices by Sector and Source* (?), and variable operation and maintenance (O&M) costs from (Akar et al., 2020). We isolate generators within WECC, our study region, using shape files of balancing areas within WECC from NREL's ReEDS model (M. Brown et al., 2020). Our initial generator fleet is described in the table S10. The *other* type of generators in the table below include geothermal, different types of waste, biomass, and other small fossil generators, which are all modeled as dispatchable capacity in the CEM and RAM.

S5.5.2.2 Generator Fleet Compression Because the existing generation fleet in WECC is large with over 4,500 units, we combine (or aggregate) existing small generators into larger generators for computational tractability. We aggregate generators within the same region using two steps and several criteria. First, for each fuel type and plant type with zero marginal costs, we aggregate all generators into a single generator by region. Zero marginal cost generators include all geothermal, wind, solar, landfill gas, municipal solid waste, biomass, and non-fossil waste generators. Second, for each fuel type and plant type with non-zero marginal costs, we aggregate generators based on age and heat rate to preserve heterogeneity in operational costs. These non-zero marginal cost

units include distillate fuel oil, natural gas combined cycle, natural gas combustion turbine, residual fuel oil, and coal (including bituminous, sub-bituminous, and lignite) generators. Specifically, by region, plant type, and fuel type, we divide generators into 4 heat rate blocks, then aggregate generators together within each heat rate block by decade between 1975 and 2026. We aggregate generators up to 200 MW in size in this manner, and create combined generators of up to 10,000 MW. These size thresholds significantly reduce the size of the generator fleet while still individually modeling mid- to large-sized power plants. Heat rates and CO₂ emission rates of the aggregated generators equal the capacity-weighted heat rates and CO₂ emission rates of their constituent generators.

S5.5.3 System Topology

Our resource adequacy (RA) model uses the five regions that WECC uses to quantify resource adequacy in WECC (WECC, 2022): NWPP NW, NWPP NE, CAMX, Desert Southwest, and NWPP Central [see figure S23]. To align regions between the CE and RA models, we model these same five regions in our CE model.

Within each of these regions, we ignore transmission constraints. Between regions, we enforce transmission constraints. Given the lack of data regarding transmission constraints between our WECC resource adequacy regions, we estimate inter-regional transmission constraints using data from the National Renewable Energy Laboratory (NREL) Regional Energy Deployment System (ReEDS) model. ReEDS provides transmission constraints between 35 balancing areas across WECC. We assign each balancing area to a region using spatial overlays, then set transmission constraints between each pair of regions as the sum of transmission constraints between each pair of balancing areas within each region. Using this method, we identify seven inter-regional, bi-directional transmission constraints. For each of these seven inter-regional transmission constraints, we limit daily inter-regional electricity transfers to an upper capacity bound.

In addition to enforcing existing transmission constraints, the CE model can also invest in new transmission capacity between each of the seven inter-regional transmission interfaces identified above. Similar to other macro-scale planning models (Jenkins & Sepulveda, 2017), we assume costs scale linearly with new transmission capacity, allowing us to maintain a computationally tractable linear program (LP). Per-MW costs of transmission expansion equal the distance (in miles) between the two centroids of in-

Transmission Capacity between	Total Capacity (GW)	Expansion Cost (1000\$/MW)
NWPP-NW and NWPP-NE	12.3	474
NWPP-NW and CAMX	7.1	1,018
NWPP-NW and NWPP-Central	1.5	569
NWPP-NE and NWPP-Central	6.0	431
CAMX and Desert Southwest	3.0	1,070
CAMX and NWPP-Central	4.6	816
Desert Southwest and NWPP-Central	5.6	348

Table S11: Transmission Networks within WECC

1236 terconnected regions times the per MW-mile cost of each bi-directional transmission line.
 1237 We estimate this cost as the median of costs between each pair of balancing authorities
 1238 between regions, which is taken from NREL's ReEDS Model's open access github (NREL,
 1239 2020). Table S11 depicts all possible combinations of aggregate links between our five
 1240 load regions and their respective aggregate capacities and total cost per MW.

1241 S5.6 WECC subregions

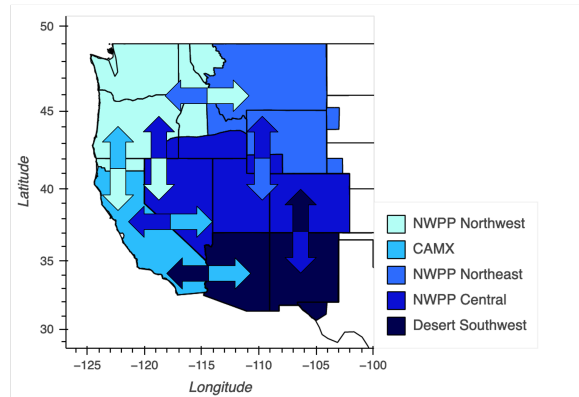


Figure S23: WECC subregions used in the CEM and RAM. Arrows show transmission flows between the subregions.

S5.7 Model Code and Data Availability

CEM code and data are available at <https://github.com/ASSET-Lab/WesternUSRDM>.

S6 Economic Dispatch Model

To calculate daily SAC and 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, CO₂ emission, inter-regional transmission, and ENS costs by optimizing generation, inter-regional transmission, and ENS decision variables. Our EDM divides WECC into the same five regions as our CEM. Supply and demand are balanced within each region while accounting for energy exchanges between regions. For computational tractability, the EDM aggregates geothermal, waste, biomass, and other small fossil plants of small capacities within each plant type together (these plant types are denoted as *other* plant type in our results).

S6.1 Functional Forms

S6.1.1 Parameters and Variables

S6.2 Objective Function

The EDM model's objective function is:

$$\begin{aligned}
 TC^{EDM} = & \sum_{i,t} p_{i,t} \times (OC_i + HR_i \times ER_i^{CO_2} \times CP) + \sum_{z,t} ens_{z,t} \times CENS \\
 & + \sum_{l,t} f_{l,t} \times FLC \quad \forall i \in \mathbb{I}, l \in \mathbb{L}, z \in \mathbb{Z}
 \end{aligned} \tag{25}$$

where t indexes time intervals (days); i indexes existing units, or all generators that are operational at the end of the CEM run (i.e., existing units at the start of the CEM run plus new investments made in the CEM run); l indexes transmission lines; z indexes regions; p is electricity generation (MWh); OC is operational cost (\$/MWh); HR is heat rate (MMBtu/MWh); ER is CO₂ emissions rate (ton/MMBtu); CP is CO₂ emissions price (\$/ton); ens is energy not served (MWh); $CENS$ is cost of energy not served (\$/MWh); FLC is the cost of electricity flows between regions (\$/MWh); and f is electricity flows between regions (MWh). The $CENS$ is set large enough to be the energy of last resort in the model (or \$1000 per MWh), while the FLC is set to \$1/MWh to incentivize balancing within regions before relying on imports or exports. OC is defined as:

Parameter	Definition	Unit
P_i^{MAX}	Maximum power rating of existing unit i	MW
P_l^{MAX}	Maximum transmission capacity of line l	MW
VOM_i	Variable O&M cost of existing unit i	\$/MWh
OC_i	Operational cost of existing unit i	\$/MWh
FC_i	Fuel cost of existing unit i	\$/MMBtu
HR_i	Heat rate of existing unit i	MMBtu/MWh
$ER_i^{CO_2}$	CO ₂ emissions rate of existing unit i	ton/MMBtu
CP	CO ₂ emissions price	\$/ton
$D_{z,t}$	Total load (or electricity demand) in region z at time t	MWh
$P_{t,z}^{MAX,WIND}$	Maximum aggregate wind profile in region z at time t	MW
$P_{t,z}^{MAX,SOLAR}$	Maximum aggregate solar profile in region z at time t	MW
$H_{b,z}$	Maximum hydropower generation in region z and month b	MWh
$FOR_{i,t}$	Forced outage rate of existing unit i at time t	—
$DR_{i,t}$	Capacity derate of existing unit i at time t	—
$CENS$	Cost of energy not served	\$/MWh
FLC	Cost of electricity flows between regions	\$/MWh
ν	Transmission losses per unit of electricity transferred between regions	%

Table S12: List of Parameters (Continued)

Set	Definition	Index	Note
$\mathbb{I}$	Set of existing units	i	–
$\mathbb{I}_z$	Set of existing units in region z	i_z	$\mathbb{I}_z \in \mathbb{I}$
$\mathbb{I}_r$	Set of existing renewable units	i_r	$\mathbb{I}_r \in \mathbb{I}$
$\mathbb{I}_w$	Set of existing wind units	i_w	$\mathbb{I}_w \in \mathbb{I}$
$\mathbb{I}_{w_z}$	Set of existing wind units in region z	i_{w_z}	$\mathbb{I}_{w_z} \in \mathbb{I}_w$
$\mathbb{I}_o$	Set of existing solar units	i_o	$\mathbb{I}_o \in \mathbb{I}$
$\mathbb{I}_{o_z}$	Set of existing solar units in region z	i_{o_z}	$\mathbb{I}_{o_z} \in \mathbb{I}_o$
$\mathbb{L}$	Set of transmission lines	l	–
$\mathbb{L}_z^{OUT}$	Set of transmission lines flowing out of region z	l_z^{OUT}	$\mathbb{L}_z^{OUT} \in \mathbb{L}$
$\mathbb{L}_z^{IN}$	Set of transmission lines flowing into region z	l_z^{IN}	$\mathbb{L}_z^{IN} \in \mathbb{L}$
$\mathbb{B}$	Set of months	b	–
$\mathbb{T}$	Set of days	t	–
$\mathbb{Z}$	Set of regions in WECC	z	–

Table S13: List of Sets

Variable	Definition	Unit
$p_{i,t}$	Electricity generation from existing unit i at time t	MWh
$ens_{z,t}$	Energy not served in region z at time t	MWh
$f_{l,t}$	Total electricity flow in line l at time t	MWh

Table S14: List of Variables

$$OC_i = VOM_i + HR_i \times FC_i \quad \forall i \in \mathbb{I} \quad (26)$$

where VOM is variable O&M costs (\$/MWh) and FC is fuel cost (\$/MMBtu).

S6.3 Constraints

The EDM requires supply balance demand at each time step in each region:

$$D_{z,t} + ens_{z,t} + \sum_{l_z^{OUT} \in \mathbb{L}_z^{OUT}} f_{l_z^{OUT},t} \leq \sum_{i_z \in \mathbb{I}_z} p_{i_z,t} + \sum_{l_z^{IN} \in \mathbb{L}_z^{IN}} f_{l_z^{IN},t} \times \nu, \quad (27)$$

$$\forall z \in \mathbb{Z}, t \in \mathbb{T},$$

where i_z indexes existing units in region z , l_z^{IN} indexes lines flowing out of region z , l_z^{OUT} indexes transmission lines flowing out of region z , ν indicates losses for each unit of electricity imported into a region (assumed to be 5%, and only applied to inflows to avoid double counting of losses), and f is electricity flows along transmission lines.

The total electricity flow through a transmission line ($f_{l,t}$) cannot exceed the line's transmission capacity (P_l^{MAX}):

$$f_{l,t} \leq P_l^{MAX}, \quad \forall l \in \mathbb{L}, t \in \mathbb{T}, \quad (28)$$

where l indexes transmission lines, and $f_{l,t}$ is total electricity flow in line l at time t (MWh).

Electricity generation by each generator is limited by its capacity derated to account for thermal deratings (DR) when relevant and for forced outage rates (FOR):

$$p_{i,t} \leq (1 - DR_{i,t}) \times (1 - FOR_{i,t}) \times P_i^{MAX}, \quad \forall t \in \mathbb{T}, i \in \mathbb{I} \quad (29a)$$

We account for thermal deratings for combustion turbines, NGCCs, and coal-fired power plants, and FORs for all generators (Section SI.S4). FORs are applied for all units; wind and solar are assumed to have a 5% FOR, while all other units have temperature-dependent forced outage rates (Section SI.S4).

Combined electricity generation by wind and solar generators is limited to aggregate wind and solar generation profiles derated by a forced outage rate (FOR) set to 5%:

$$\sum_{i_{wz} \in \mathbb{I}_{wz}} p_{i_{wz},t} \leq P_{z,t}^{MAX,WIND} \times (1 - FOR), \quad \forall t \in \mathbb{T}, z \in \mathbb{Z}, \quad (30a)$$

$$\sum_{i_{oz} \in \mathbb{I}_{oz}} p_{i_{oz},t} \leq P_{z,t}^{MAX,SOLAR} \times (1 - FOR), \quad \forall t \in \mathbb{T}, z \in \mathbb{Z}, \quad (30b)$$

Hydropower generation is constrained based on observed data for each of our weather years. Since we ignore transmission constraints within each of our five regions, we aggregate hydropower capacity by region, then limit total hydropower generation by month (or time block):

$$\sum_{t_b \in T_b, i_{h_z} \in I_{h_z}} p_{i_{h_z}, t_b} \leq H_{b,z}, \forall z \in \mathbb{Z}, b \in \mathbb{B} \quad (31)$$

where i_{h_z} indexes all hydropower units in region z and $H_{b,z}$ equals maximum total hydropower generation in month b and region z .

S6.4 Model Code and Data Availability

EDM code and data are available at <https://github.com/atpham88/US-CE>.

S7 Surplus Available Capacity

We calculate SAC as:

$$\begin{aligned} SAC_{z,t} = & \sum_{i_z \in \mathbb{I}_z} AvailableNonHydroCapacity_{i_z,t} \\ & + HydropowerGeneration_{z,t} + TransmissionImports_{z,t} \\ & - TransmissionExports_{z,t} - Demand_{z,t}, \end{aligned} \quad (32)$$

$$\forall z \in \mathbb{Z}, T \in \mathbb{T}$$

Hydropower generation and transmission imports and exports are optimized outputs from the EDM. Optimized hydropower generation accounts for temperature-dependent FORs (Table S6) and monthly energy budgets (Section S2.4). Available non-hydropower capacity accounts for several factors. In the case of wind and solar, it accounts for wind and solar capacity factors and an assumed 5% FOR (Table S6). For all other non-hydropower plants, it accounts for temperature dependent FORs and, in the case of fossil-based thermal plants (combustion turbines, NGCCs, and coal-fired power plants), thermal deratings (Table S6).