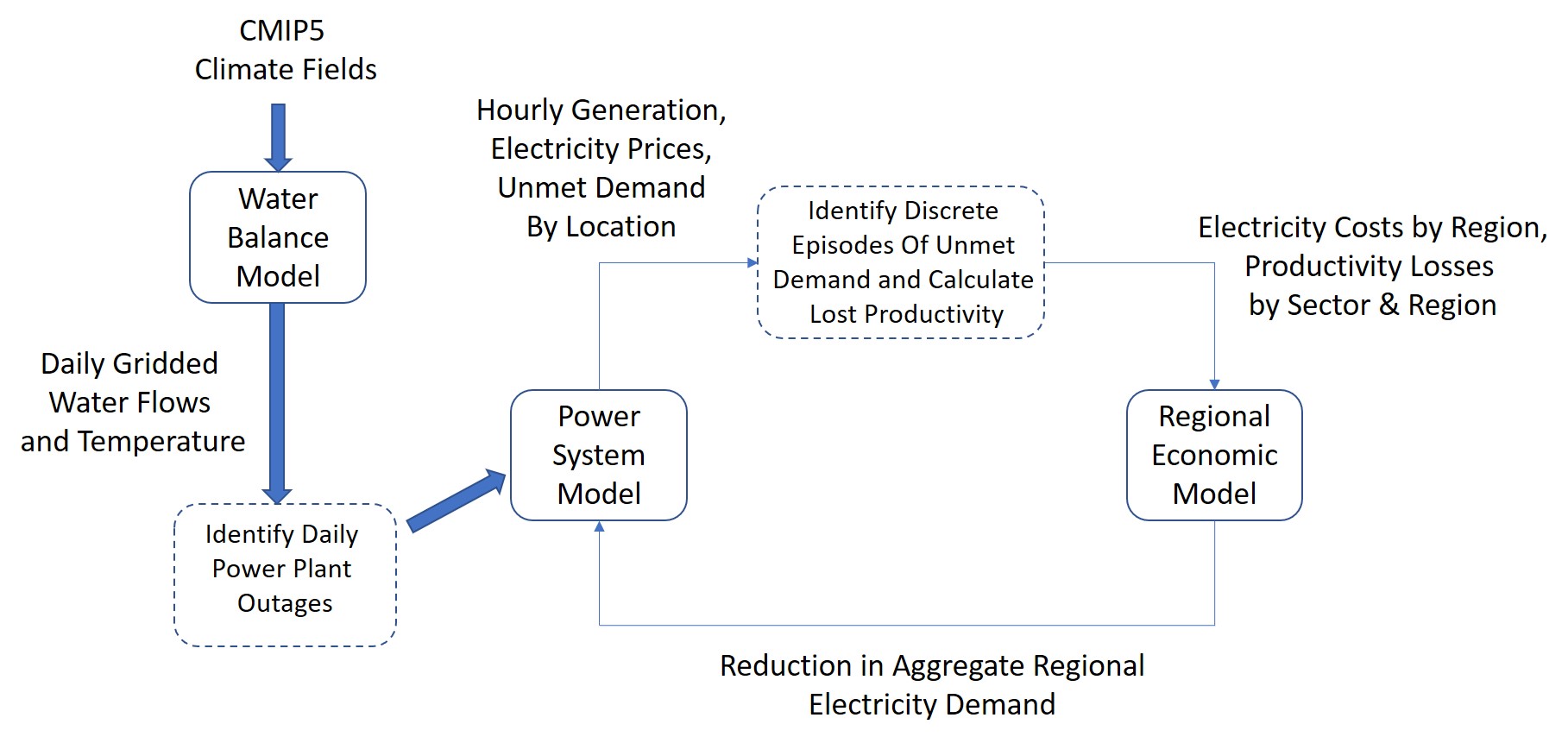
**SUPPLEMENTARY INFORMATION**

**Methodology**

In this section, we describe the data, models, and methods used in the analysis. The integrated water-power-economy modeling framework consists of a water balance model, a detailed power system model with high spatial and temporal resolution, and a state-level economy-wide model of the U.S. The main elements of the model framework are shown in Figure S1. The model simulates the economic impacts from water temperatures for a hypothetical future year. Downscaled climate fields from CMIP5 drive the water balance model, which simulates 2006-2099 in daily time steps. The daily gridded water temperatures for one year of these simulations are used to determine which (if any) electricity generators are not available each day because the water temperature threshold has been reached. The power system model then simulates the hypothetical year in hourly time steps, constrained by generator outages. The power system model provides hourly generation for each power plant, hourly electricity costs at each location in the network, and hourly electricity demand that could not be met (if any) at each location. The hourly unmet demand is analyzed to identify the number of distinct unmet demand events at each location, and the duration and magnitude of each event. Productivity loss from the unmet demand events is estimated by applying the results from a large survey of the costs of electricity interruption to US industrial sectors. The productivity losses and the electricity costs are inputs to the regional economy model. If electricity costs are higher than the benchmark (no water stress) case, substitution by producers and consumers of other inputs for electricity result in less electricity demand. The power system model is then solved again with the lower demand levels, which will result in lower costs and less unmet demand than the previous iteration. The power system and economic models iterate in this process until the demand reduction from the economic model does not change from the previous iterations. Below, we describe each model component and how the components interact.



***Figure S1****: Water-Power-Economy Model framework.*

**Power Plant Database**

The data and assumptions for the Western Electricity Coordinating Council (WECC) case are described in detail in the Power System Model section. Power plants in WECC that require water for cooling and their latitude and longitude were identified from the data sources.1,2,3 For WECC power plants located in Canada and Mexico, additional data sources from WECC (such as a names data set and the Loads and Resources database) were used to geolocate some of the plants. The remaining plants were identified manually using Internet searches and Google Earth was used to verify their placement. All power plants that require water were then overlaid on the 6-arc minute gridded digital river network and placed in the appropriate grid cell representing the plant location. This step adjusts for the potential mismatch between the actual cooling water source and digital river lines that result from gridded discretization of the river network. These locations were then used to sample the river temperature fields output by the Water Balance Model (WBM).

**Water Balance Model (WBM)**

We simulated the water temperature scenarios in the WECC region using the University of New Hampshire Water Balance Model (WBM).4,5 The WBM is a process-based, spatially distributed, gridded model that simulates the natural movement of water at a daily time step through local processes and along the river network and includes glacier runoff from Huss and Hock.6 WBM also simulates the human controls on the water cycle through agricultural water use, dams and reservoirs, and inter-basin hydrological transfers. River water temperature is also tracked and altered through the river network7 and is based on the equilibrium temperature model of Dingman.8

To arrive at the river temperatures needed for the latter half of the 21st Century, WBM was initialized with a spin-up period and a transient historical run using the MERRA-2 climate drivers.9 Because the objective of this study was to demonstrate an illustrative range of patterns, we focused on the output from two CMIP5 Global Circulations Models (GCMs) to drive the WBM runs: CCSM4 and GFDL-CM3 over the years 2006-2099 for RCP 8.5.

Due to the coarse resolution of the GCMs, we used a nested method of spatial downscaling similar to the methods in Mishra et al.,10 which is particularly important in the high elevation mountain regions of the US West. A bi-linear interpolation was applied to the temperature and precipitation fields from each of the models. This gave a higher-resolution grid scale matching WBM’s 6 arc-minute river network resolution. An elevation-based correction was applied to each of the temperature fields using a lapse rate of -6.4 °C km-1 of elevation guided by Rennick11 and using the elevation difference between the high-resolution river network and the lower-resolution geopotential layer of the climate driver. This resulted in elevation-based temperature variation at sub-climate driver resolution. In addition to downscaling, we also applied the delta-change bias correction method to the GCM monthly time step climate drivers by applying to each grid cell the monthly climatology difference between MERRA-2 and the corresponding GCM fields. For precipitation, the delta change was applied to a constant daily variability over each month, using year 2001 values. A constant monthly temperature was used by WBM; however, river temperature and river flow were output at daily steps to provide a set of yearly samples from which to draw for modeling the power system.

**Power Systems Model (PSM)**

Power systems models for long term planning and integration with other system models have traditionally been modeled using an aggregated representation of the power system with coarser spatial and/or temporal resolution.12,13,14 However, with increases in renewable energy deployment, it is necessary to obtain higher spatial and temporal resolution in power systems modeling for better understanding of its impacts on the economy. Because renewable generation is variable and the dispatchable thermal generation technologies have constraints and costs associated with how their output changes over time, it is necessary to have some representation of the chronological hourly patterns of demand and renewable generation. These intertemporal operating constraints cannot be easily captured using a non-chronological load duration curve with representative hours.15,16,17,18 Similarly, the same aggregate demand and set of generators can have widely varying outcomes depending on how the demand and generation is distributed spatially across the network and on the specific characteristics of the network lines.

The Power System Model (PSM) in this study is a chronological hourly model with detailed engineering constraints. To ensure computational tractability and represent operational and detailed transmission constraints, the PSM combines a unit commitment (UC) model with an optimal power flow (OPF) model that resolves individual generators and resolves the high-voltage transmission grid. The UC model simulates the day-ahead scheduling of units and enforces the intertemporal operating constraints and zonal constraints on transmission flows, and the OPF model simulates the real-time hourly dispatching of the scheduled units and enforces the transmission and power flow constraints.

The unit commitment model solves for a 168-hour (1 week) schedule for the on/off status and output level of all generators by minimizing total variable costs subject to supply meeting demand and the operational constraints. The total variable cost includes the generation cost (fuel and non-fuel) and start-up costs. The operational constraints of the generators include the minimum time that the generator must be online/offline (minimum uptime/downtime); the maximum rate at which each generator can adjust its output (ramp up/down limits); the minimum and maximum output levels of the generator when online; and a minimum level of system-wide slack to increase output (spinning reserves). There are also binary constraints specifying whether the generator is available or not. The binary constraints are modeled to determine the status of the generator in that time period. There are three binary variables: startup, shutdown, and whether the plant is on or off. The model is formulated as a mixed-integer linear programming model and is based on the tight and compact formulation in Morales-Espana et al.19,20

After the UC model determines which units are online in each hour, the realized level of generation from each unit is determined by the OPF model, which minimizes total variable cost subject to demand and transmission constraints. These constraints include the maximum/minimum generating capacity of each unit; maximum transmission capacity; the physical flow of power over the transmission lines; and electricity demand. This model uses a linear approximation of the power flow equations, the DC-OPF formulation, which assumes that the differences in bus phase angles are relatively small and that all voltages are close to their setpoint; a common assumption for offline simulations of large power systems. The DC-OPF model is formulated as a linear programming model as in Munoz et al.21 and Bukenberger and Webster.22

Our case study is based on the WECC, the high-voltage transmission network that covers roughly the western third of the continental U.S. as well as parts of western Canada and northern Mexico. The data and network representation for this case was developed by the Johns Hopkins University,1,2,21,23,24 using methods developed by Shi25. The model case consists of 3569 generators, of which 2011 are renewable sources and 1558 are conventional generation sources. The UC model approximates transmission constraints using a zonal partition that aggregates buses (network nodes) into the 13 zones corresponding to states with Oregon and Washington as a single zone and aggregate transmission lines into 36 transmission paths between the zones using a transport (directed flow) representation. The network model for WECC in the OPF model is a 312-bus aggregation of the WECC network with 654 transmission lines between the buses. Demand, renewable data, and transmission line data are obtained from WECC.26,27 The generators consist of 17 different fuel types. Generator-specific parameters are taken from a combination of the eGrid 20163 database, the original reduced network WECC case, and generic assumptions based on fuel and prime mover. In the PSM model, unserved electricity demand is penalized at $1,000 per MWh to ensure feasible solutions that minimize unmet demand. As described further below, the coupled energy-economy model values unmet demand with region and industry-specific damage functions that estimates the productivity loss due to unserved energy events by sector, season, day of week, time of day, and duration of event. For each year simulated, we solve for 8736 chronological hours (52 weeks) as 52 separate 168-hour simulations to take advantage of parallel computing.

The results of a complete simulation of the power system for one iteration consists of an 8736-hour time series of the hourly output of every generator in the model, the hourly marginal cost of energy at every bus location, and the hourly unmet electricity demand at every bus location. The model coupling (described below), aggregates this data for input into the regional economic model.

**Regional Economic Model (REM)**

The regional economic model (REM) used in our analysis is a static inter-regional computable general equilibrium (CGE) model of the United States. The model is based on the modeling framework of Rausch and Rutherford,28 which calibrates the model to the IMPLAN U.S. state-level accounts.29 In this analysis, we develop a model that allows for the simulation of impacts on sector productivity and demand for goods and services. The CGE modeling approach used in this analysis provides a flexible and theoretically rigorous platform for modeling impacts at the sector level and aggregates sectoral responses to the economy as a whole while capturing general equilibrium and multiplier effects.30,31,32

In the model, all interactions of the four economic agents—consumers, producers, government, and the trade sector—are captured. Consumers are endowed with a supply of labor and capital that are employed by firms as factors of production. Firms purchase these factors at a price determined by the supply and demand (i.e. market) for those factors. Firms transform these factors of production into commodities that are either purchased by other firms as factors of production or by households as final consumption goods. A competitive equilibrium exists when prices equate supply and demand in all markets, producers earn no excess profit, and consumers exhaust all income. These are the three principles that govern general equilibrium theory. By specifying functional form and elasticities of substitution between inputs and goods, these three principles guide all interaction within the simulated economy.

The production sector comprises a total of ten producing sectors (agriculture; mining; construction; manufacturing; electric power; telecommunications and utilities; trade and retail; finance, insurance and real estate; services) plus the public sector. The inter-industry structure of the model allows both direct and indirect effects to be captured. The production technology is assumed to exhibit constant returns to scale and firms are assumed to maximize profits.

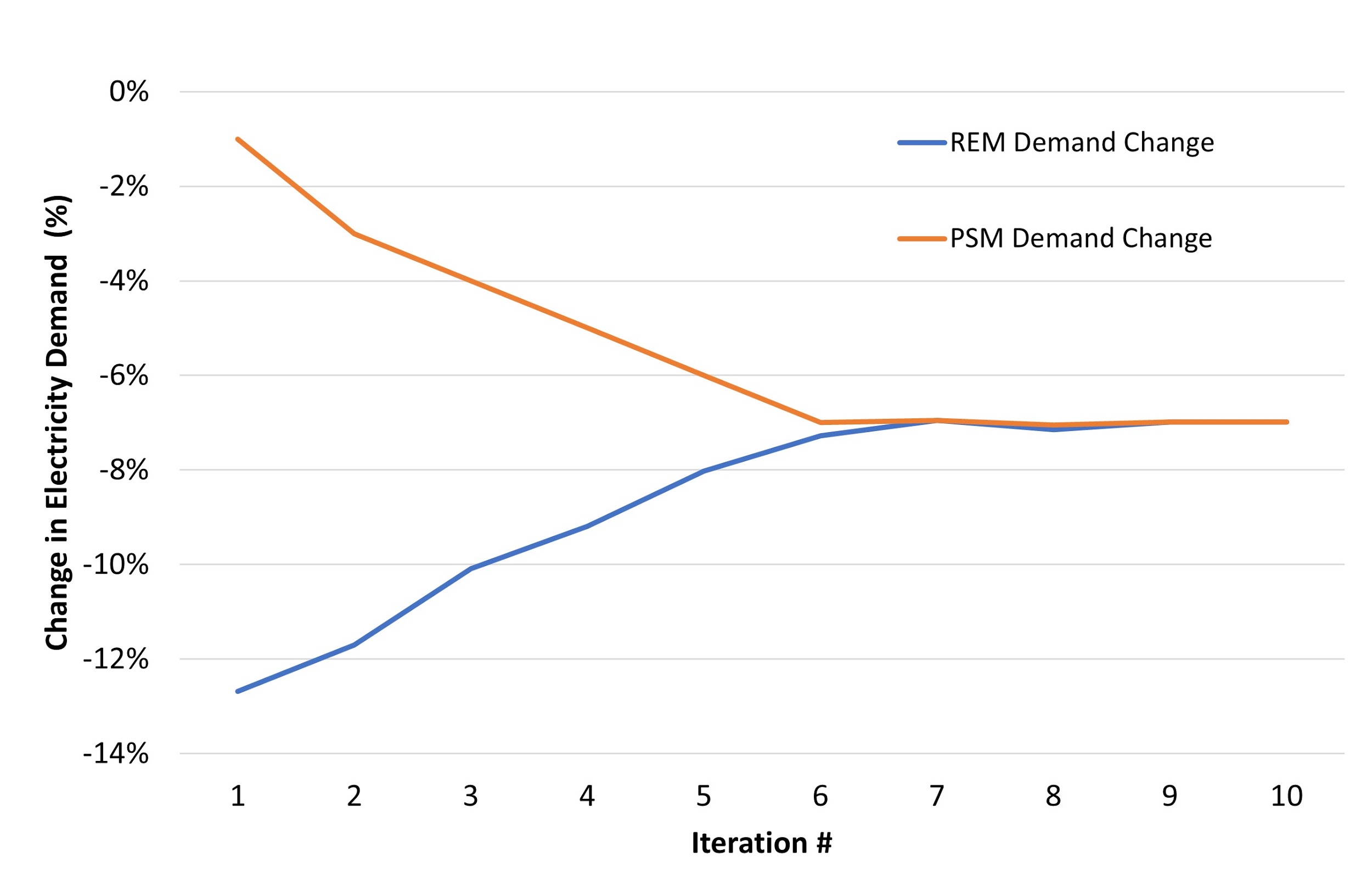
Consumer demand for each of the nine commodities is determined by utility maximization, where household income is derived from labor income, capital income and transfers. The government sector collects taxes and uses the revenue to purchase goods and services. The trade sector is modeled using the standard one-country Armington approach,33 which assumes that domestic and imported goods are imperfect substitutes. There are three regions represented in the model: California (CA), the rest of the West (ROW) (AZ, CO, ID, MT, NE, NM, NV, OR, UT, WA, WY), and the rest of the U.S (ROUS). Both intra- and international trade are represented in the model, with trade flows influenced by differences in relative prices for goods and services across regions.

The primary sources of data for the construction of model parameters are state-level social accounting matrices (SAM) for 2010 from IMPLAN29 (formally known as the Minnesota IMPLAN group (MIG)). These state-level SAMs are constructed using data from sources such as the Bureau of Economic Analysis (BEA), the Bureau of Labor Statistics (BLS), and the US Census. These social accounting matrices trace the flow of commodities and payments across all sectors of the regional economy in a given benchmark year. From this we derive the labor and capital incomes, the tax revenue by type of tax, and the expenditures on specific commodities by the household, government, and foreign sectors.

**Electricity-Economy Coupling Methodology**

An exogenous shock to the power system, such as generation capacity outages because of higher water temperatures, will result in changes in electricity generation cost by region. The cost increase is implemented in the regional economic model as a shock to the productivity of the electricity sector in that region, which will result in a shift in electricity use by other sectors that use electricity as an input to production as well as by final consumers. The demand reduction within the economic model in response to the higher cost must be communicated to the power system model, which then repeats the dispatch of electricity for the entire year to meet the new lower electricity demand pattern. Each iteration of the power system model with lower demand than the previous iteration will result in lower electricity costs and less unmet demand. This process iterates until the marginal loss from the electricity cost increase is equal to the marginal loss from reducing demand further; equilibrium is achieved when there is no benefit to changing electricity demand from the previous iteration.

We apply the coupling methodology of Böhringer and Rutherford34 to find the equilibrium reduction in electricity demand. Because of the non-linear response of the economic model, we employ a standard gradient search algorithm to achieve convergence. Figure S2 shows one example from our simulations of the convergence, based on the scenario from WBM for GFDL-CM3 2094. The demand reduction imposed in the PSM is adjusted gradually to approach the demand reduction estimated from REM. Equilibrium is achieved when the demand reduction in both models are equal and when this value does not change between consecutive iterations.



***Figure S2****: Convergence of coupled PSM-REM model; results for case: GFDL-CM3 2094.*

Results from the PSM are aggregated for input to REM as follows. The marginal cost of electricity by bus by hour is first aggregated spatially to obtain an hourly time series of average hourly cost for all buses in California (CA) and the average hourly cost for all remaining buses in the Rest of WECC (ROW). Because the REM model has annual time steps, we then compute the annual average cost for CA and for ROW as a weighted average of the hourly cost and the hourly generation for the specific region. When the shock is applied and unmet demand is present, the prices for the hours with unmet demand at each bus is substituted with the cost of the most expensive generator in the region. In this case study the highest cost generators are diesel generators with a cost of $268 per MWh. The annual average cost for each region is then used to find the percentage change relative to the solution to the benchmark case with no generation outages from water temperatures. The percentage change in annual electricity cost for CA and ROW are inputs to the next iteration of REM.

The results from REM for the next iteration of the PSM are the percentage reduction in electricity demand in CA and in ROW. The electricity demand in the PSM is based on historical hourly demand by bus for the year 2014. This demand pattern is used in the initial simulation of each water scenario. Subsequent iterations of PSM for that scenario apply the annual percentage reduction in demand to obtain a new hourly demand at every bus. The reduction for CA is used for every bus in that region, and the reduction for ROW is applied to all remaining buses. The new hourly demand pattern is the input to the next iteration of the PSM.

**Impacts from Unserved Electricity Demand**

In addition to the increase in electricity cost, unmet electricity demand results in productivity losses in the economic model. To capture the impacts of unserved electricity on the producing sectors from a shock to the power system, we apply the customer damage functions developed by Sullivan et al.35 In this work, the authors develop a meta-dataset that combines survey results on electricity customer interruption costs from a number of studies. The dataset comprises responses from ~12,000 firms and ~8,000 households. Using the firm data, the authors estimate a two-part model to predict firm interruption cost by sector, season, day of week, time of day, and duration of outage. First, a limited dependent model is estimated that predicts the probability that the firm will report zero interruption costs. Second, interruption costs are regressed on a set of independent variables for those firms reporting non-zero costs. The probabilities from the limited dependent variable estimation are combined with the coefficients from the second regression to generate interruption cost predictions.

The results show that interruption costs of a one-hour outage are highest: (1) for manufacturing firms; (2) for firms in the West and Southeast; and (3) on summer weekday afternoons. We also find that annual interruptions costs are higher in a year with multiple short duration outages than in a year with a few longer duration outages, since in cases of long duration outages, firms can shut down production and send employees home while this is not possible in short duration outages. The procedure for transforming the hourly spatial patterns of unmet electricity demand into annual productivity losses by sector by region is as follows. The first step aggregates the unmet demand, in units of MWh for each hour and each bus, by summing the total hourly unmet demand over all buses in each region, CA and ROW. The total electricity demand is also summed over all buses in each region. Next, the hourly pattern for each region is analyzed by counting discrete unmet demand events. A discrete event is defined as a consecutive sequence of one or more hours of non-zero unmet demand and is separated from other events by at least one hour of no unmet demand before and after the event. All events are recorded separately with three associated pieces of information: the duration of the event (the number of hours), the average magnitude of the event as measured by the total unmet energy as a percentage of the total unmet demand over that sequence of hours, and the season, day-of-week, and time-of-day that the event occurs. We use the definitions of season, day-of-week, and time-of-day from Sullivan et al.,35 which specifies different loss coefficients for each of 32 time slices: 4 times of day (morning, afternoon, evening, overnight) x 2 day-types (weekday, weekend) x 4 seasons (spring, summer, winter, fall). Each hour is assigned to one of the 32 time slices, and if there is an unserved demand event in that hour, it uses the appropriate loss coefficient.

The total annual reduction in productivity from each sector in each region is calculated as follows. The productivity loss from each discrete event for one sector of one region is determined by multiplying the average magnitude of the event (% of demand that was unmet during the event) by a season-day-time-specific scaling factor and by a sector-specific scaling factor (see Sullivan et al., 2009 for the estimates of these factors). The total annual sectoral loss for each region is obtained from summing over all events in that region. The damage magnitude varies with the duration of the event. We apply different scaling factors for time and sector depending on whether the event had a duration of 1 hour, 2-4 hours, or 5 or more hours.

The above procedure produces a table of productivity shocks for each sector in the REM model for each region, CA and ROW. The productivity shocks corresponding to the most recent PSM simulation are imposed in the next iteration of REM.

**Climate and Water Stress Scenarios**

In the main text, we show results for a set of 18 one-year water temperature scenarios. Each scenario consists of daily gridded water temperatures from one year of a simulation of WBM as forced by the downscaled climate fields from one of a set of CMIP-5 Global Circulation Model results for RCP 8.5. The scenarios analyzed in detail are drawn from transient runs of WBM for the years 2041-2099 as forced by the climate fields from GFDL-CM3 and from CCSM4. To facilitate one-year simulations of the coupled power-economy model, each year of WBM output is treated as a distinct scenario. All generators in the WECC dataset for the PSM model have an associated latitude-longitude, from which each generator is matched to the nearest spatial grid location in WBM. We analyzed the full set of one-year scenarios from WBM to convert the daily water temperature to hourly generator outages, which provides the input to the PSM for that scenario.

Each one-year simulation consists of 52 weeks, with each week consisting of seven days or 7x24=168 hours. A simulated year is therefore 52x168=8736 hours. The capacity outage pattern for each scenario is a matrix of 8736 hours by 478 generators (the number of thermal generators in the WECC case that require water for cooling). To summarize the aggregate outage impacts for all scenarios from the GFDL-CM3 and CCSM4 cases, we show in Figure S3 a scatterplot relating the number of hours that at least one generator is unavailable because of the water temperature threshold and the average hourly magnitude of the unavailable capacity, averaged over only the hours in which the outage capacity is non-zero. A third aggregate metric for each scenario is the maximum capacity unavailable in any hour over the year. Table S1 shows these three aggregate measures for all 118 scenarios (constructed from the WBM output for 2014-2099 for the GFDL-CM3 and the CCSM4 climate forcings). Note that Table S1 is in two columns and is sorted by the overall magnitude of the outage impact, from the smallest in the first row on the left side to the largest impact on the last row of the right side of the table.

We find that simulating the outages for all scenarios with fewer than 1400 hours and average outage capacity of less than 2200 MW result in increases of electricity cost of less than 0.2% and zero unmet demand. After the economic model reaches equilibrium, the impacts of all these scenarios are less the 0.01%, and therefore are not significant. We therefore focus in the main text on 18 scenarios with larger impacts on capacity outages.

**Sectoral Economic Impacts of Extreme Water Temperatures**

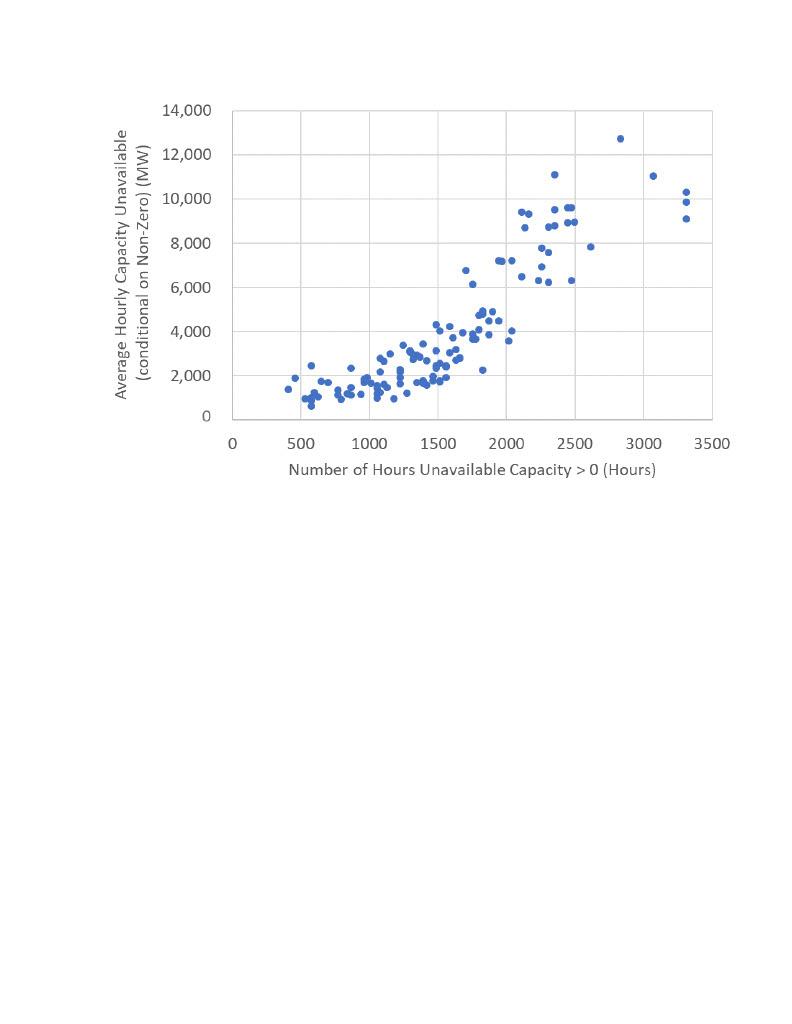
Table S2 presents the impacts on the change in production from each sector of the model with results for the 18 water temperature scenarios that produce an impact of -0.01% or greater. All other scenarios from Table S1 lead to impacts that are smaller than this level. The REM represents California and an aggregate of the rest of WECC and includes the sectoral impacts for both regions. The results for the equilibrium solution are given, representing the PSM and REM convergence to a final electricity demand level and include the productivity impacts from unmet electricity demand in the equilibrium solution. The results in Figure 3 in the main text correspond to the GFDL 2089 case, although that figure presented the initial impact before the economic adjustment.

For the scenarios analyzed, the impacts on California for all sectors are significantly less than the impacts on the Rest of WECC. The sector with the greatest loss of productivity in the Rest of WECC is Manufacturing, for which the largest change is -1.17%, followed by the Mining sector (which includes crude oil and natural gas production) with changes as much as -0.84%. Moderate impacts occur for the Agricultural, Retail, and Public Services sectors.

**Generation Outages and Unmet Electricity Demands**

Table S3 presents the total generation capacity outage amount by state as a result of higher water temperatures on specific days and the total annual unmet electricity demand by state. The capacity outages shown are the averages for those hours with non-zero values and summed over all generators located in that state. The unmet demand, in units of MWh, is summed over all network locations in the state from the PSM’s reduced WECC network model and over all hours of the year.

The results in Table S3 demonstrate that for the 18 water temperature scenarios analyzed, some states, such as California and Utah, have significant generation capacity outages but experience very little unmet demand. In contrast, Colorado has less generation capacity outage than other states but has the most unmet demand. For the most severe water temperature scenarios, unmet demand also occurs in Arizona in the model. Note that the spatial pattern of unmet demand results from the interaction of the particular transmission network topography, the spatial patterns of the historical electricity demand and solar and wind generation, and the spatial patterns of temperature and precipitation from the GFDL-CM3 RCP8.5 climate fields. Changes to the network topography or to the spatio-temporal patterns of climate fields or electricity demand could alter the specific locations where unmet demand occurs when the system is sufficiently stressed. The relevant insight from these results is not the specific location of impacts in these simulations, but rather that a regional external stress pattern from weather or climate will be transmitted through the coupled water and power system networks to other locations that are the most vulnerable, usually because of bottlenecks at intermediate points in the networks.



***Figure S3****: Generation capacity unavailable because of water temperature threshold. Each marker represents a one-year scenario of daily gridded water temperatures from WBM as driven by one of the CMIP-5 RCP 8.5 climate fields. This figure shows the results for WBM scenarios for 2041-2099 as forced by GFDL-CM3 RCP 8.5 or by CCSM4 RCP 8.5. X-axis shows the total number of hours in that year that at least one generator is unavailable due to the water temperature threshold. The Y-axis indicates the hourly capacity in MW that is unavailable averaged over all hours for which this value is non-zero.*

***Table S1****: The number of hours with non-zero generation capacity unavailable, the capacity unavailable averaged over all hours for which this is non-zero, and the maximum capacity unavailable in any one hour for each scenario of water temperatures from WBM. Scenarios are ordered in table from the smallest impacts on outages in the first row of the left half of the table to the largest impacts on the last row of the right half of the table.*

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **MODEL** | **YEAR** | **HOURS OUTAGE** | **AVG OUTAGE** | **Max OUTAGE** | **MODEL** | **YEAR** | **HOURS OUTAGE** | **AVG OUTAGE** | **Max OUTAGE** |
| CCSM4 | 2049 | 576 | 880 | 3,568 | CCSM4 | 2095 | 1560 | 2,388 | 13,654 |
| CCSM4 | 2057 | 528 | 959 | 3,529 | CCSM4 | 2080 | 1512 | 2,574 | 11,329 |
| CCSM4 | 2079 | 576 | 627 | 3,068 | CCSM4 | 2097 | 1560 | 2,422 | 9,073 |
| CCSM4 | 2062 | 576 | 1,017 | 3,372 | GFDL | 2045 | 1560 | 2,467 | 10,490 |
| CCSM4 | 2046 | 624 | 1,062 | 3,497 | CCSM4 | 2084 | 1392 | 3,434 | 15,455 |
| CCSM4 | 2068 | 792 | 929 | 3,625 | CCSM4 | 2067 | 1632 | 2,700 | 14,495 |
| GFDL | 2044 | 408 | 1,393 | 3,675 | GFDL | 2068 | 1488 | 3,143 | 15,956 |
| CCSM4 | 2063 | 768 | 1,123 | 6,351 | GFDL | 2060 | 1824 | 2,270 | 13,599 |
| CCSM4 | 2056 | 600 | 1,258 | 4,040 | CCSM4 | 2072 | 1656 | 2,783 | 14,784 |
| CCSM4 | 2047 | 840 | 1,178 | 7,834 | CCSM4 | 2086 | 1584 | 3,054 | 17,011 |
| CCSM4 | 2052 | 864 | 1,144 | 4,828 | GFDL | 2095 | 1656 | 2,828 | 10,381 |
| CCSM4 | 2042 | 768 | 1,350 | 6,323 | GFDL | 2041 | 1488 | 4,324 | 19,517 |
| CCSM4 | 2050 | 936 | 1,172 | 6,344 | GFDL | 2050 | 1632 | 3,176 | 14,350 |
| CCSM4 | 2088 | 1056 | 982 | 4,477 | CCSM4 | 2094 | 1512 | 4,029 | 17,196 |
| CCSM4 | 2045 | 864 | 1,474 | 9,031 | CCSM4 | 2091 | 1608 | 3,735 | 18,336 |
| CCSM4 | 2053 | 1056 | 1,186 | 6,657 | GFDL | 2071 | 1584 | 4,240 | 14,916 |
| CCSM4 | 2041 | 456 | 1,905 | 7,334 | GFDL | 2055 | 1752 | 3,672 | 14,760 |
| CCSM4 | 2087 | 1176 | 977 | 3,811 | GFDL | 2057 | 1776 | 3,664 | 15,015 |
| GFDL | 2058 | 696 | 1,700 | 7,800 | GFDL | 2059 | 1680 | 3,937 | 20,649 |
| GFDL | 2046 | 648 | 1,755 | 8,059 | CCSM4 | 2078 | 1752 | 3,877 | 17,267 |
| CCSM4 | 2043 | 1056 | 1,454 | 8,854 | CCSM4 | 2093 | 1872 | 3,851 | 19,283 |
| CCSM4 | 2069 | 1080 | 1,240 | 10,283 | GFDL | 2056 | 1800 | 4,086 | 16,654 |
| CCSM4 | 2058 | 960 | 1,687 | 7,750 | GFDL | 2061 | 2016 | 3,571 | 13,554 |
| CCSM4 | 2064 | 1056 | 1,544 | 5,963 | GFDL | 2042 | 1800 | 4,741 | 17,532 |
| CCSM4 | 2051 | 1008 | 1,662 | 12,293 | GFDL | 2074 | 1752 | 6,143 | 27,533 |
| CCSM4 | 2059 | 1128 | 1,461 | 8,851 | GFDL | 2049 | 1824 | 4,804 | 17,209 |
| CCSM4 | 2044 | 576 | 2,451 | 7,634 | GFDL | 2065 | 1704 | 6,749 | 25,205 |
| CCSM4 | 2085 | 1272 | 1,212 | 8,314 | GFDL | 2063 | 1872 | 4,479 | 16,408 |
| GFDL | 2053 | 1104 | 1,619 | 7,917 | GFDL | 2052 | 2040 | 4,023 | 19,932 |
| CCSM4 | 2061 | 960 | 1,837 | 9,952 | GFDL | 2066 | 1824 | 4,945 | 21,095 |
| CCSM4 | 2074 | 984 | 1,933 | 9,668 | GFDL | 2079 | 1944 | 4,479 | 19,354 |
| CCSM4 | 2090 | 1224 | 1,637 | 7,883 | GFDL | 2077 | 1896 | 4,890 | 16,297 |
| CCSM4 | 2071 | 864 | 2,336 | 12,018 | GFDL | 2076 | 1944 | 7,204 | 27,492 |
| CCSM4 | 2054 | 1080 | 2,163 | 12,697 | GFDL | 2087 | 1968 | 7,172 | 25,838 |
| CCSM4 | 2065 | 1224 | 1,915 | 11,512 | GFDL | 2072 | 2112 | 6,482 | 20,649 |
| CCSM4 | 2089 | 1416 | 1,581 | 7,374 | GFDL | 2084 | 2232 | 6,301 | 25,201 |
| CCSM4 | 2075 | 1392 | 1,671 | 9,279 | GFDL | 2073 | 2304 | 6,223 | 20,499 |
| CCSM4 | 2083 | 1344 | 1,710 | 8,735 | GFDL | 2085 | 2040 | 7,224 | 23,083 |
| CCSM4 | 2060 | 1224 | 2,284 | 16,710 | GFDL | 2070 | 2256 | 6,917 | 24,855 |
| GFDL | 2067 | 1224 | 2,187 | 8,908 | GFDL | 2091 | 2136 | 8,702 | 24,729 |
| CCSM4 | 2076 | 1392 | 1,793 | 9,938 | GFDL | 2064 | 2256 | 7,773 | 22,543 |
| CCSM4 | 2073 | 1104 | 2,667 | 12,567 | GFDL | 2069 | 2472 | 6,321 | 25,101 |
| CCSM4 | 2048 | 1080 | 2,806 | 10,996 | GFDL | 2080 | 2304 | 7,572 | 20,392 |
| CCSM4 | 2098 | 1464 | 1,771 | 11,817 | GFDL | 2083 | 2112 | 9,397 | 26,576 |
| CCSM4 | 2077 | 1512 | 1,789 | 13,288 | GFDL | 2093 | 2160 | 9,309 | 26,298 |
| GFDL | 2043 | 1512 | 1,731 | 6,647 | GFDL | 2088 | 2304 | 8,742 | 29,714 |
| CCSM4 | 2096 | 1464 | 1,986 | 9,261 | GFDL | 2082 | 2352 | 8,784 | 29,922 |
| CCSM4 | 2055 | 1152 | 2,988 | 12,147 | GFDL | 2078 | 2448 | 8,932 | 33,771 |
| CCSM4 | 2081 | 1320 | 2,749 | 17,088 | GFDL | 2081 | 2616 | 7,823 | 25,385 |
| CCSM4 | 2092 | 1488 | 2,346 | 8,569 | GFDL | 2086 | 2352 | 9,504 | 37,361 |
| CCSM4 | 2082 | 1488 | 2,450 | 11,958 | GFDL | 2089 | 2496 | 8,943 | 27,857 |
| GFDL | 2054 | 1560 | 1,929 | 9,100 | GFDL | 2098 | 2448 | 9,587 | 31,441 |
| CCSM4 | 2066 | 1296 | 3,090 | 14,995 | GFDL | 2075 | 2352 | 11,090 | 38,085 |
| GFDL | 2047 | 1320 | 2,950 | 11,222 | GFDL | 2096 | 2472 | 9,592 | 29,882 |
| GFDL | 2062 | 1416 | 2,672 | 10,761 | GFDL | 2092 | 3312 | 9,087 | 32,679 |
| CCSM4 | 2099 | 1368 | 2,864 | 13,727 | GFDL | 2090 | 3312 | 10,311 | 39,432 |
| GFDL | 2048 | 1344 | 2,934 | 13,176 | GFDL | 2099 | 3072 | 11,037 | 36,511 |
| CCSM4 | 2070 | 1248 | 3,398 | 14,716 | GFDL | 2094 | 3312 | 9,841 | 38,831 |
| GFDL | 2051 | 1296 | 3,137 | 18,367 | GFDL | 2097 | 2832 | 12,733 | 43,766 |

***Table S2****: Percentage production change by sector for each scenario for California (top) and for Rest of WECC (bottom).*

|  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| California | | | | | | | | | | | |
| MODEL | **YEAR** | **Financial** | **Agric.** | **Mining** | **Construction** | **Manuf.** | **Elec.** | **Utility** | **Retail** | **Services** | **Public** |
| GFDL | 2045 | -0.01% | 0.00% | 0.00% | 0.00% | -0.01% | 0.01% | -0.01% | -0.01% | -0.01% | 0.00% |
| GFDL | 2050 | 0.00% | 0.00% | 0.00% | 0.00% | 0.00% | 0.05% | 0.00% | 0.00% | 0.00% | 0.00% |
| GFDL | 2061 | 0.00% | 0.00% | 0.02% | 0.00% | 0.01% | 0.04% | 0.00% | 0.00% | 0.00% | 0.00% |
| GFDL | 2077 | -0.01% | -0.01% | 0.02% | 0.00% | 0.00% | 0.13% | -0.01% | -0.01% | -0.01% | -0.01% |
| GFDL | 2085 | -0.01% | -0.01% | 0.04% | -0.01% | 0.02% | 0.12% | -0.01% | -0.01% | -0.01% | -0.01% |
| GFDL | 2081 | -0.01% | -0.02% | 0.04% | -0.01% | 0.01% | 0.14% | -0.01% | -0.01% | -0.01% | -0.01% |
| GFDL | 2078 | -0.01% | -0.02% | 0.04% | -0.01% | 0.02% | 0.13% | -0.01% | -0.01% | -0.01% | -0.01% |
| GFDL | 2089 | -0.02% | -0.02% | 0.06% | -0.01% | 0.03% | 0.14% | -0.02% | -0.01% | -0.01% | -0.02% |
| GFDL | 2092 | -0.03% | -0.04% | 0.09% | -0.01% | 0.03% | 0.17% | -0.03% | -0.02% | -0.02% | -0.03% |
| GFDL | 2083 | -0.01% | -0.01% | 0.03% | 0.00% | 0.01% | 0.11% | -0.01% | -0.01% | -0.01% | -0.01% |
| GFDL | 2086 | -0.02% | -0.02% | 0.06% | -0.01% | 0.02% | 0.11% | -0.02% | -0.01% | -0.01% | -0.02% |
| GFDL | 2098 | -0.01% | -0.02% | 0.04% | -0.01% | 0.01% | 0.12% | -0.01% | -0.01% | -0.01% | -0.01% |
| GFDL | 2096 | -0.02% | -0.03% | 0.06% | -0.01% | 0.02% | 0.11% | -0.02% | -0.02% | -0.01% | -0.02% |
| GFDL | 2094 | -0.13% | -0.15% | 0.24% | -0.04% | 0.00% | -0.35% | -0.10% | -0.13% | -0.07% | -0.07% |
| GFDL | 2090 | -0.04% | -0.05% | 0.09% | -0.02% | 0.02% | 0.11% | -0.03% | -0.03% | -0.02% | -0.03% |
| GFDL | 2099 | -0.05% | -0.07% | 0.14% | -0.02% | 0.04% | 0.03% | -0.04% | -0.04% | -0.03% | -0.04% |
| GFDL | 2075 | -0.02% | -0.03% | 0.06% | -0.01% | 0.02% | 0.14% | -0.02% | -0.02% | -0.01% | -0.02% |
| GFDL | 2097 | -0.06% | -0.08% | 0.15% | -0.03% | 0.04% | 0.03% | -0.05% | -0.05% | -0.03% | -0.04% |
| Rest of WECC | | | | | | | | | | | |
| MODEL | **YEAR** | **Financial** | **Agric.** | **Mining** | **Construction** | **Manuf.** | **Elec.** | **Utility** | **Retail** | **Services** | **Public** |
| GFDL | 2045 | 0.00% | -0.01% | 0.00% | 0.00% | 0.00% | 0.04% | 0.00% | 0.00% | 0.00% | 0.00% |
| GFDL | 2050 | -0.01% | -0.02% | 0.01% | 0.00% | -0.01% | 0.09% | 0.00% | -0.01% | 0.00% | -0.01% |
| GFDL | 2061 | -0.05% | -0.05% | -0.17% | 0.00% | -0.23% | 0.01% | -0.02% | -0.08% | -0.03% | -0.07% |
| GFDL | 2077 | -0.09% | -0.10% | -0.24% | -0.01% | -0.34% | 0.15% | -0.04% | -0.13% | -0.05% | -0.10% |
| GFDL | 2085 | -0.11% | -0.12% | -0.32% | -0.01% | -0.45% | 0.14% | -0.05% | -0.17% | -0.07% | -0.13% |
| GFDL | 2081 | -0.10% | -0.12% | -0.25% | -0.01% | -0.38% | 0.28% | -0.04% | -0.15% | -0.06% | -0.12% |
| GFDL | 2078 | -0.11% | -0.13% | -0.31% | -0.01% | -0.45% | 0.22% | -0.05% | -0.17% | -0.07% | -0.14% |
| GFDL | 2089 | -0.17% | -0.18% | -0.51% | -0.01% | -0.71% | 0.21% | -0.07% | -0.27% | -0.11% | -0.21% |
| GFDL | 2092 | -0.22% | -0.23% | -0.64% | -0.02% | -0.91% | 0.32% | -0.09% | -0.35% | -0.14% | -0.27% |
| GFDL | 2083 | -0.06% | -0.09% | -0.13% | 0.00% | -0.22% | 0.26% | -0.03% | -0.09% | -0.04% | -0.07% |
| GFDL | 2086 | -0.14% | -0.15% | -0.40% | -0.01% | -0.57% | 0.24% | -0.06% | -0.22% | -0.09% | -0.17% |
| GFDL | 2098 | -0.11% | -0.12% | -0.29% | -0.01% | -0.43% | 0.23% | -0.05% | -0.17% | -0.07% | -0.13% |
| GFDL | 2096 | -0.14% | -0.15% | -0.39% | -0.01% | -0.56% | 0.23% | -0.06% | -0.22% | -0.09% | -0.17% |
| GFDL | 2094 | -0.26% | -0.38% | -0.43% | -0.01% | -0.86% | 1.50% | -0.11% | -0.38% | -0.15% | -0.30% |
| GFDL | 2090 | -0.17% | -0.21% | -0.43% | -0.01% | -0.66% | 0.50% | -0.07% | -0.26% | -0.10% | -0.20% |
| GFDL | 2099 | -0.27% | -0.27% | -0.84% | -0.02% | -1.17% | 0.34% | -0.12% | -0.44% | -0.18% | -0.34% |
| GFDL | 2075 | -0.15% | -0.17% | -0.43% | -0.01% | -0.62% | 0.28% | -0.06% | -0.24% | -0.09% | -0.19% |
| GFDL | 2097 | -0.28% | -0.30% | -0.82% | -0.02% | -1.17% | 0.49% | -0.12% | -0.44% | -0.18% | -0.35% |

***Table S3****: Generation capacity outage and total annual unmet demand by state for each scenario.*

|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  |  | New Mexico | | Arizona | | Nevada | | California | | Utah | | WA/OR | | Montana | | Wyoming | | Colorado | |
| MODEL | **YEAR** | Cap. Outage  (MW) | Unmet Demand  (MWh) | Cap. Outage  (MW) | Unmet Demand  (MWh) | Cap. Outage  (MW) | Unmet Demand  (MWh) | Cap. Outage  (MW) | Unmet Demand  (MWh) | Cap. Outage  (MW) | Unmet Demand  (MWh) | Cap. Outage  (MW) | Unmet Demand  (MWh) | Cap. Outage  (MW) | Unmet Demand  (MWh) | Cap. Outage  (MW) | Unmet Demand  (MWh) | Cap. Outage  (MW) | Unmet Demand  (MWh) |
| GFDL | 2045 | 361 | 0 | 1762 | 0 | 933 | 0 | 1324 | 114 | 1136 | 0 | 50 | 0 | 0 | 0 | 552 | 0 | 19 | 0 |
| GFDL | 2050 | 161 | 0 | 3119 | 0 | 673 | 0 | 1043 | 0 | 1494 | 0 | 55 | 0 | 0 | 0 | 0 | 0 | 19 | 0 |
| GFDL | 2061 | 379 | 0 | 2839 | 0 | 1183 | 0 | 1098 | 0 | 1271 | 0 | 50 | 0 | 173 | 0 | 552 | 0 | 1066 | 5046 |
| GFDL | 2077 | 735 | 0 | 3173 | 0 | 1051 | 0 | 1147 | 124 | 1780 | 0 | 180 | 0 | 155 | 0 | 640 | 0 | 1168 | 6899 |
| GFDL | 2085 | 591 | 0 | 4231 | 0 | 853 | 0 | 1895 | 9 | 1670 | 0 | 342 | 0 | 281 | 0 | 817 | 0 | 1382 | 9098 |
| GFDL | 2081 | 1024 | 0 | 4756 | 0 | 1426 | 0 | 1924 | 0 | 1503 | 0 | 96 | 0 | 146 | 0 | 628 | 0 | 1326 | 10880 |
| GFDL | 2078 | 871 | 0 | 5035 | 273 | 1563 | 0 | 2356 | 0 | 1691 | 0 | 57 | 0 | 173 | 0 | 729 | 0 | 1547 | 12720 |
| GFDL | 2089 | 498 | 0 | 5236 | 0 | 1007 | 0 | 2318 | 0 | 1627 | 0 | 186 | 0 | 542 | 0 | 741 | 0 | 1660 | 16869 |
| GFDL | 2092 | 670 | 0 | 5538 | 26 | 1387 | 0 | 2467 | 47 | 1581 | 0 | 394 | 0 | 689 | 0 | 793 | 0 | 1769 | 31648 |
| GFDL | 2083 | 607 | 0 | 5289 | 0 | 890 | 0 | 2266 | 8 | 1507 | 0 | 147 | 0 | 148 | 0 | 640 | 0 | 1342 | 3592 |
| GFDL | 2086 | 701 | 0 | 6369 | 0 | 1226 | 0 | 2827 | 0 | 1658 | 0 | 141 | 0 | 173 | 0 | 686 | 0 | 1528 | 17431 |
| GFDL | 2098 | 738 | 0 | 5405 | 582 | 1445 | 0 | 2390 | 0 | 1688 | 0 | 93 | 0 | 173 | 0 | 552 | 0 | 937 | 9213 |
| GFDL | 2096 | 495 | 0 | 5415 | 0 | 1709 | 0 | 2637 | 14 | 1590 | 0 | 72 | 0 | 166 | 0 | 590 | 0 | 1129 | 14549 |
| GFDL | 2094 | 1122 | 0 | 6349 | 10929 | 1517 | 0 | 2602 | 0 | 1602 | 0 | 86 | 0 | 171 | 0 | 703 | 0 | 1408 | 5750 |
| GFDL | 2090 | 1313 | 0 | 6873 | 10166 | 1423 | 0 | 2418 | 0 | 1587 | 0 | 365 | 0 | 227 | 0 | 856 | 0 | 1422 | 10453 |
| GFDL | 2099 | 1140 | 0 | 7170 | 12695 | 1804 | 0 | 2989 | 0 | 1383 | 0 | 398 | 0 | 572 | 0 | 790 | 0 | 1801 | 21410 |
| GFDL | 2075 | 977 | 0 | 6455 | 1371 | 1847 | 0 | 3156 | 6 | 1655 | 0 | 80 | 0 | 165 | 0 | 658 | 0 | 1603 | 15364 |
| GFDL | 2097 | 1392 | 0 | 7525 | 15878 | 1764 | 0 | 3347 | 0 | 1728 | 0 | 302 | 0 | 823 | 0 | 853 | 0 | 1731 | 24840 |

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