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The Role of Regional Connections in Planning for Future Power System Operations Under Climate Extremes

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Special Section:
Modeling MultiSector Dynamics to Inform Adaptive Pathways

The Role of Regional Connections in Planning for Future Power System Operations Under Climate Extremes

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Key Points:

- Contemporary and future Western U.S. power grids are evaluated with stochastic and historically based compound climate extreme scenarios
- Drought has most impact on simulated generation mix and production cost; load changes under heat have more impact on regional power flow
- Total summer regional power flows decrease in the future power system simulations, but power flows remain critical during peak hours

Supporting Information:

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

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Abstract Identifying the sensitivity of future power systems to climate extremes must consider the concurrent effects of changing climate and evolving power systems. We investigated the sensitivity of a Western U.S. power system to isolated and combined heat and drought when it has low (5%) and moderate (31%) variable renewable energy shares, representing historic and future systems. We used an electricity operational model combined with a model of historically extreme drought (for hydropower and freshwater-reliant thermoelectric generators) over the Western U.S. and a synthetic, regionally extreme heat event in Southern California (for thermoelectric generators and electricity load). We found that the drought has the highest impact on summertime production cost (+10% to +12%), while temperature-based deratings have minimal effect (at most +1%). The Southern California heat wave scenario impacting load increases summertime regional net imports to Southern California by 10–14%, while the drought decreases them by 6–12%. Combined heat and drought conditions have a moderate effect on imports to Southern California (−2%) in the historic system and a stronger effect (+8%) in the future system. Southern California dependence on other regions decreases in the summertime with the moderate increase in variable renewable energy (−34% imports), but hourly peak regional imports are maintained under those infrastructure changes. By combining synthetic and historically driven conditions to test two infrastructures, we consolidate the importance of considering compounded heat wave and drought in planning studies and suggest that region-to-region energy transfers during peak periods are key to optimal operations under climate extremes.

1. Introduction

Past heat and drought events have stressed the electricity grid in the U.S. through generation cost and electricity price increases (Bramer et al., 2017; Christian-Smith et al., 2015; Harto et al., 2012; Kern et al., 2020; Voisin et al., 2018) and, rarely, widespread outages (California ISO, 2021). Climate change is expected to increase the frequency and intensity of heat waves in the U.S. (USGCRP, 2017). Further, the risk of hot-dry extremes in the contiguous U.S. has already increased over the last century (Alizadeh et al., 2020). Specifically in California where hydrometeorological conditions already drive price volatility (Su, Kern, Reed, & Characklis, 2020), climate change has increased the risk for low-precipitation events that are also warm (Diffenbaugh et al., 2015). Because these changes are happening at the same time that power systems are evolving toward more renewables, there is a need to incorporate climate impacts in electricity system planning (Coughlin & Goldman, 2008; Craig et al., 2018; Peter, 2019; Ralston Fonseca et al., 2021).

Historical analysis of drought and heat impacts on the Western grid are available in a few cases. Harto et al. (2012) reviewed historical droughts, including the 2001 and 1977 historical Western U.S. droughts, and found that hydroelectric power was limited more severely than thermoelectric power and systems were able to compensate by purchasing power. The impacts of drought were manifest in increased prices and emissions but not in reliability. Christian-Smith et al. (2015) considered adaptations to the multiyear 2007–2009 drought in California and found that electricity imports and natural gas generation increased. Both Harto et al. (2012) and Scanlon et al. (2013) state that drought duration increases electricity system vulnerability and arid regions may actually be less drought vulnerable because of power plant design. An August 2020 heat wave caused rolling outages of 15–150 min during two evenings in California, affecting about 500,000 customers. Widespread heat throughout the Western U.S. and deficient planning and operational practices caused the outages, but the extent of the outages was mitigated by coordinated conservation efforts (California ISO, 2021). However, our ability to plan according to the historical record is limited because extreme heat and drought events, especially combined, are uncommon in the historical record of electricity system operations.

Capturing the effect of multiple and synchronous climate and weather changes in energy models is a complex multisector dynamics problem because it usually involves translating those stressors onto grid processes across multiple temporal and spatial scales and representing the linkages of Earth and human systems. Despite varying methods and combinations of other climate or weather stressors included, such as transmission line deratings, thermoelectric generator deratings and outages, increased electricity demand, hydroelectric reductions, and renewable resource changes (Table S1 in Supporting Information S1),when electricity demand changes are compared with other stressors, they are typically the strongest driver of the electricity system changes (Jaglom et al., 2014; Ralston Fonseca et al., 2021; Steinberg et al., 2020; Totschnig et al., 2017; Wang et al., 2016), with the possible exception of significant renewable resource changes (Peter, 2019). Droughts, however, could accentuate the impact of high temperature on grid operations (Voisin et al., 2016, 2018) because more than 25% of the generation in the Western U.S. grid is water-dependent. The contemporary Western U.S. grid has been evaluated across a number of angles including sensitivity of generation, transmission, and demand to climate change (Bartos & Chester, 2015); sensitivity of grid operations and regional dependencies to changes in historical water availability (Voisin et al., 2018) compounded with fuel price volatility (O'Connell et al., 2019) or future water availability (Voisin et al., 2020b); sensitivity of regional grid operations to compounded variability of hydrometeorological drivers (Su, Kern, Reed, & Characklis, 2020); regional dependencies driven by market and climate change (Hill et al., 2021); and sensitivity of operations to stream and air temperatures (Miara et al., 2017). However, the relevance of historical models and infrastructures is quickly fading as power systems change.

Changes in the Western U.S. infrastructure have been modeled along with heat, drought, or their combination. Using capacity expansion modeling of the U.S., Jaglom et al. (2014) and McFarland et al. (2015) show that the capital costs of emissions mitigation pathways should be quantified only relative to the fuel cost increases required to meet demand without mitigation. Jaglom et al. (2014) also found that increased electricity demand changes regional energy flows. Steinberg et al. (2020) compared isolated and combined climate change impacts on the future U.S. infrastructure build-out and found that demand is the key driver of energy expansion and economic impacts at the national level. At a regional level, Steinberg et al. (2020) found that regional climate does not directly drive regional generation due to the interconnectedness of the power system. Miara et al. (2019) iteratively adjusted infrastructure build-outs based on climate-water feedbacks and found that climate-adjusted U.S. infrastructures have 5–12% higher capacity and may be more reliable than nonadjusted infrastructures, but they did not test using operational models. Using an operational model, Turner et al. (2019) explored two potential infrastructures in the Northwest U.S. for the year 2035 and found that combined hydropower seasonality change and load increases and shifts resulted in electricity shortfalls not observed in isolated effects. Tarroja et al. (2016) used operational models of a future California grid that uses 50% renewable generation and found that the increase in hydroelectric variability due to climate change increases operational costs and other grid metrics. Tarroja et al. (2019) further explored a highly renewable California system and found that hydroelectric variability due to climate change has minimal impacts on renewable generation but increases the need for dispatchable capacity and increases generation costs. Wessel (2022) stress-tested future Western U.S. grid infrastructure for the evolving 2035–2050 horizon with 100 synthetically generated weather years demonstrating that "bad weather years" were still dominated by drought conditions even under high renewables portfolio.

Computational resources are often a challenge and to stress test the Western U.S. system with thousands of combinations of infrastructure, wind, solar, hydro, and load requires some simplification such as statistical representations of regional power flow dependencies (Su, Kern, Denaro, et al., 2020), a reduced domain (Tarroja et al., 2016; Turner et al., 2019), a reduced resolution for the hydropower dispatch (Turner et al., 2019; Wessel et al., 2022), and reduced number of stress test (Miara et al., 2019). Those advances were critical in demonstrating the importance of regional dependencies. Higher resolution modeling across the entire domain is needed to address questions across stakeholders. Modeling heat and drought in future power systems challenges modelers to capture decadal-scale changes in infrastructure and climate along with heat and drought events that operate on timescales from days to years. Only Peter (2019), modeling Europe, examined heat, drought, and other stress impacts on infrastructure evolution in combination with high-resolution operational power models. A decrease in wind and solar resources in the study dominated changes in generation mix and increases in generation costs. Water-limited coal and nuclear power was a secondary and important factor, and hydropower and demand impacts were smallest and were heterogenous across regions. When these changes were anticipated in planning, more gas and offshore wind were planned, and the total of capital and operating costs was reduced by 2% compared to when changes were not anticipated.

This paper considers the importance of power sector changes *along with* heat and drought stress in a high-resolution operational power system model. Our primary research question is: *What are the impacts of temperature and drought extremes on the operation of the Western U.S. grid as the penetration of variable renewable energy (VRE) on the system increases?* Specifically:

1. What is the *sensitivity* of a primarily thermal power grid to drought and heat, in isolation and in combination?
2. What are the *changes in sensitivity* to drought and heat when the system has a higher penetration of variable renewable energy?

Those questions have been addressed by others over the Western U.S. context with a range of technical choices associated with the computational limits challenges to address angles of the science questions (Oikonomou et al., 2022). We specifically aim for insights—and data sets—that can inform multiple stakeholders at both utility and system scale and thus the high-resolution power system model is needed. We thus specifically address the challenge of representing compounding events by generating hybrid stochastic temperature scenarios while representing droughts, which are more complex to represent stochastically and tend to drive the overall stress as demonstrated by previous studies, with a stakeholder relevant historical drought. We demonstrate a method to distinguish the power system impacts of drought, heat, and infrastructure changes using a highly resolved power system model with an engineered subset of compounded heat wave and drought events. In this paper, the heat scenario is from a stochastic temperature time series generated from the historical record, and the drought scenario—affecting both hydropower and fresh surface water-dependent thermoelectric plants—is based on a historically extreme drought. Contributing to the study albeit not the main point of the analysis, we also improve on the typical model resolution by using county-level temperature forcings, water constraints resolved at individual power plants, zonal power transmission (over 400 zones nonetheless), and hourly dispatch at the generator level.

2. Methods

We tested the sensitivity of two Western U.S. power system infrastructure scenarios to electricity supply and demand-side stress based on one extreme heat and one drought scenario that are modeled based on a consistent gridded observed meteorological data set (Maurer et al., 2002). The simulated temperature and hydrological extremes fed into models for electricity demand, temperature-sensitive power plants, hydroelectric generation, and water-sensitive power plants, which ultimately force electricity operation simulations (Figure 1). The models were connected by passing data between models.

2.1. Electricity System

We modeled heat and drought impacts on two Western U.S. infrastructures, a historical and future case, representing the change from primarily thermal to significantly variable renewable energy generation (Table 1 and Figure S1 in Supporting Information S1). The historical infrastructure ("low variable renewable") is based on the approximate 2010 power plant fleet as in O'Connell et al. (2019), having 5% variable renewable (VRE) generation. We chose a hypothetical future infrastructure with 31% variable renewable generation using a combination of scenarios from (Brinkman et al., 2016) to create a future higher renewables scenario across the entire Western U.S. ("moderate variable renewable"). The infrastructure assumptions from Brinkman et al. are a combination of variable renewable, conventional thermal, storage, demand response, and energy efficiency plausible for the year 2030 given existing technology, known thermal plant retirement schedules, and load growth estimates. Here we increased load and reserve requirements uniformly (i.e., without changing the load shape) by 12.5% from the low variable renewable system (2010 load) to the moderate variable renewable (future) system, according to the future load growth assumed in Brinkman et al. (2016). For comparison to our 5% and 31% variable renewable penetration infrastructures, in 2018 the variable renewable penetration of the Western Interconnection was 12% (WECC, 2020), while more aggressive decarbonization pathways for the U.S. require over 70% carbon-free electricity (mostly wind and solar) by 2035 (Larson et al., 2020; Phadke et al., 2020). Note that in the Western

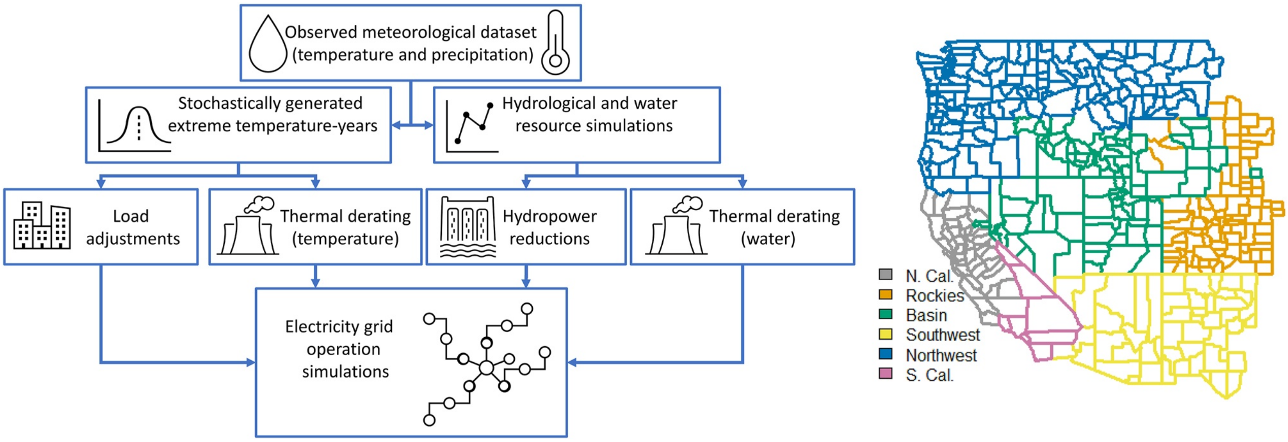

Figure 1. Summary of model linkages (left) and model regions with county-level resolution (right). The electricity model has county-level transmission and load resolution and is described by six reserve sharing regions (plus portions of Canada and Mexico, not shown). Those connected portions of Canada and Mexico are included in the simulation but not adjusted according to heat or drought scenarios. Because regions are actually reserve sharing regions in the model that are comprised of a set of nodes and associated generators that participate in reserve sharing, the county-to-region mapping shown here is based on assigning each county to the region where the most nodes participate. Apparent discontinuities in the Basin-Rockies regions are not consequential, as these counties have very little generating capacity.

U.S., hydrocapacity is a significant source of flexible capacity, whose capacity goes largely unchanged in the two infrastructures we studied, and is not considered a variable renewable.

We employed hourly production cost simulations of each electricity infrastructure that minimized total production costs for each day during each 1-year simulation. We used a mixed integer linear program formulation that accounts for the unit commitment decisions of thermal power plants including generator-level ramp rates, start-up times, and start-up costs. The electricity load and transmission limits were aggregated to the county level as described in O'Connell (2019). We simulated the Western U.S. (Figure 1) with minimal interchange with the Eastern Interconnection, and we included the connected portions of the Western U.S., Canada, and Mexico, but the Canada and Mexico power plants and load sensitivity to the extremes were not represented. We selected a west-wide domain to best represent regional interactions, while using a relatively resolved zonal transmission setup to reflect spatial variability of the heat events across the west. (A nodal transmission representation would further detail transmission flows but have a higher computational burden.) See the Supporting Information S1 for detail on the production cost model setup and infrastructure assumptions.

Table 1
Low and Moderate Variable Renewable Infrastructure Details

	Low (5%) VRE penetration	Moderate (31%) VRE penetration
System characteristics		
Load (TWh)	823	928
Summer load (TWh)	224	252
Peak load (GW)	143	160
Demand response (GW)	0	4
Storage (GW)	4	9
Annual energy generation (TWh)		
Hydro	225 (27%)	238 (25%)
Geothermal and biomass	40 (5%)	50 (5%)
Wind (VRE)	32 (4%)	142 (15%)
Solar (VRE)	<1 (<1%)	146 (16%)
Conventional capacity[a]	537 (64%)	356 (38%)
Total	836	941

Note. The systems are characterized as 3% and 31% variable renewable penetration determined by the wind plus solar generation divided by the total generation, where total generation does not include storage and demand response. Generation is slightly higher than load due to pumping loads related to generation.
[a]Includes gas CC, gas CT, coal, "other," nuclear, combined heat and power, and steam types.

2.2. Water Availability Stress and Impact on Generation

Representing over 300 individual hydropower plants and water constraints at over 600 thermoelectric plants requires leveraging large-scale hydrology modeling (Turner & Voisin, 2022). We examined water stress sensitivity by adjusting operations of both hydroelectric power plants and certain thermoelectric power plants for drought. We leverage previous hydrologic and water management simulations and methods for adjusting hydroelectric availability. We improve upon the hydropower representation by simulating monthly hydropower as a function of seasonal water availability.

We used macroscale, distributed hydrological and water resource simulations to constrain hydropower and thermoelectric generation at individual plants in the U.S. Only plants in Canada and Mexico outside of hydrological contributing areas into the U.S. were not adjusted for water availability. We leveraged hydrologic simulations performed using the VIC hydrology model (Liang et al., 1994) forced with a gridded observed meteorological data set (Maurer et al., 2002) as detailed in Brekke et al. (2014). The simulated distributed historical runoff is then routed through the MOSART river routing model (Li et al., 2013) coupled with the spatially distributed water management model WM (Voisin et al., 2013), which explicitly represents reservoir storage and release and withdrawals to meet spatially distributed water demands. VIC-MOSART-WM simulations have a daily time step and 1/8th degree (~12 km) spatial resolution. We leveraged VIC-MOSART-WM simulations (Voisin et al., 2020a) developed in Voisin et al. (2020b).

The 1955–2020 time series of thermoelectric plant monthly derating was leveraged from Voisin et al. (2020b). Generation for thermal plants requires a different approach than hydropower. The capacity at a thermal plant may be affected during drought either due to lack of available flow, because river water temperatures limit cooling efficiency, or because discharge water temperature limits necessitate plant turndown. These effects are difficult to capture at a large scale, primarily because we lack historical, plant-level data describing capacity derating under alternative flow conditions. In the present work, we followed the derating method of Voisin et al. (2016), wherein the summer thermal capacity was derated linearly from maximum capacity as a function of deviation in annual flow below median conditions. If flow exceeded median summer flow, no derating was applied. Since many thermal plants are located off-stream, we used simulated flows at the relevant HUC-4 outlet rather than plant locations to drive this analysis. The actual thermoelectric derating data set was leveraged from Voisin et al. (2020b).

About 75% of the hydropower generation in the production cost model simulation is assumed to have significant reservoir storage. There are tradeoffs between hydropower representation, computational resources, and data availability for power system models (Oikonomou et al., 2022), and our approach to modeling the hydropower plants with reservoir storage takes a moderately resolved approach to approximate the real, multisector constraints of hydropower operation. In this approach the production cost model uses a two-stage optimization, where first the constraints on hydropower are approximated using monthly energy budgets and the daily hydropower generation of each facility is set assuming perfect foresight on load and other resource availability. In the second stage of optimization, the power system is optimized at hourly resolution, with day-ahead perfect foresight. The minimum and maximum output (MW) and ramp rates (MW/hr) are respected at each hydropower facility, like other generator types. Monthly targets for the power system simulation were developed offline using simulated, regulated water flows at grid cells corresponding to each plant. Previous work (Voisin et al., 2016) coupling MOSART-WM with zonal power system models used a rescaling approach at individual power plants to represent interannual variability. To convert monthly flow to available energy, in this study, a simple statistical model was adopted. Using monthly, plant-level generation data (Form EIA-860 Detailed Data with Previous Form Data (EIA-860 A/860B), 2019) as the predictand, a linear model was trained for each plant and month of year. Although this model is statistical, it is analogous to a physics-based model of hydropower in the sense that the slope parameter represents the product of hydraulic head (m), the specific weight of water (N/m^3), and plant efficiency (dimensionless). Adjusting this parameter for each month provides flexibility to account for likely seasonal patterns of storage levels and controlled, nonpowered spills to meet environmental flow requirements. It is therefore unsurprising that the linear model can simulate monthly power generation with reasonable accuracy for the majority of plants and regions, and better support a coupling with operational power system model using power plant dispatch rather than zonal hydrodispatch (Figure S6 in Supporting Information S1).

About 25% of the hydropower generation was modeled in the production cost model using fixed hourly input instead of monthly available energy. For those facilities, we computed monthly available energy (as with the other hydroplants) and then disaggregated each month's energy to hourly using a historical hourly profile. These plants were therefore simulated with a fixed hourly schedule that is scaled to represent changing seasonal water conditions.

An updated 1955–2020 time series of hydropower plant monthly potential and thermoelectric plant capacity was developed (see Data Availability Statement). Both hydropower energy budgets and thermal plant derated capacities were constrained with predefined minimum and maximum levels (to avoid generating above capacity in the event of plentiful water, for instance). We selected the historical 1977 drought to compare to a nondrought year in 2005 (Figure S7 in Supporting Information S1). The modeled 1977 drought had relatively severe summertime thermoelectric water-based deratings, with 13 GW lost capacity in the low VRE system (10% of total gas CC, gas CT, and coal capacity), and because of some plant retirements, 9 GW in the moderate VRE system (7%).

2.3. Heat Stress and Impact on Generation and Load

Another novel contribution of this work is to link a stochastic simulation of temperature with high-resolution power system modeling. We used an extreme temperature simulation as inputs to model electricity load and thermoelectric power plant capacity.

2.3.1. Simulation of Alternative Temperature Years

General circulation models are limited in their ability to capture extremes (USGCRP, 2017). Some studies have developed extreme temperature scenarios for power system modeling by adding a fixed number of degrees to a historical time series (Cochran & Denholm, 2021; Ke et al., 2016; Wang et al., 2016) or adjusting peak week load estimates to match recent observed load extremes (Cochran & Denholm, 2021) or using a stochastic weather generator (Su, Kern, Denaro, et al., 2020). We take the later approach, using here a multivariate stochastic simulation model to capture a range of spatially and temporally consistent conditions with the historical period, from which we could select an extreme case. This nonparametric space-time stochastic simulator can reproduce the intensity, duration, and frequency of heat spells. The stochastic weather generator also preserves the across-site and across-variables dependence in the weather variables and provides inputs for electricity system extremes analysis. The simulations use precipitation and temperature which were also derived from Maurer et al. (2002) for consistency with the hydrological model. The data are at daily timescale and county level and cover 407 counties in the Western U.S. in a 62-year historical data set. We completed 100 simulations, resulting each of 62 years in length at daily timescale.

The simulation method (shown in Figure S9 in Supporting Information S1) involves the following two steps: (a) K-nearest neighbor based weather generation algorithm is first implemented for each county for simulating ensembles of daily rainfall, maximum temperature, and minimum temperature (weather variables; Rajagopalan & Lall, 1999); (b) The ensemble of simulated weather variables generated separately at each county are reorganized spatially using a multivariate copula (Lall et al., 2016) to enable the reproduction of spatial dependence across grids. The model has demonstrated ability to simulate data at large spatial scales. For instance, Lall et al. (2016) presented comparisons of spatially correlated livestock mortality rate data from 327 soums (counties) in Mongolia. In the current study, we simulated data for 417 counties over the Western U.S. (only 407 are later used in the electricity simulation) and key statistics were replicated well. For illustration, two example statistics are presented in Figures S10 and S11 in Supporting Information S1, which show the comparison of observed and simulated spatial correlations and heat spells. The advantage of this methodology is that it provides more iterations (user-defined number of simulations). Moreover, since the nonparametric copula framework uses a log-spline density estimation (Kooperberg & Stone, 1991) for the marginal distributions, there is the ability to simulate more extreme occurrences than are available in the historical record. See Lall et al. (2016) or Devineni and Troy (2015) and the Supporting Information S1 for more details on the stochastic model.

Because translating precipitation to water availability is nontrivial and we were interested in testing extreme combinations of heat and drought (not necessarily historical combinations of heat and drought), we used only the temperature outcomes of the stochastic model in this paper, while extreme drought was modeled based on historical conditions as described in Section 2.2. This paper provides a test case for the two-variable model and for linking the temperature simulations to power system modeling. Future work could extend the utility by adding additional variables such as wind speed and humidity or incorporating climate forcings.

From simulated temperature data, we selected an extreme temperature year. In previous studies, high temperature extremes have been identified using temperature thresholds, duration, land coverages, and other associated variables (Hawkins et al., 2017; Miller et al., 2008; Seneviratne et al., 2014; Smith et al., 2014). In this study, we selected an extreme temperature year by focusing on the 20 counties (out of 407 counties) that account for 52% of the electricity load of the Western U.S. (Figure S12 in Supporting Information S1). We focused our results on one extreme temperature year where 12 of 20 counties exceeded 35°C median temperature for 3 days, which resulted in what we refer to as the Southern California extreme heat scenario. We also identified three other extreme temperature years by selecting heat waves based on maximum temperatures above 40°C, years in which the summertime was warm overall (not necessarily with a heat wave), and years that had the highest temperature deviation from the reference year. See the Supporting Information S1 for details on selection of extreme temperature years.

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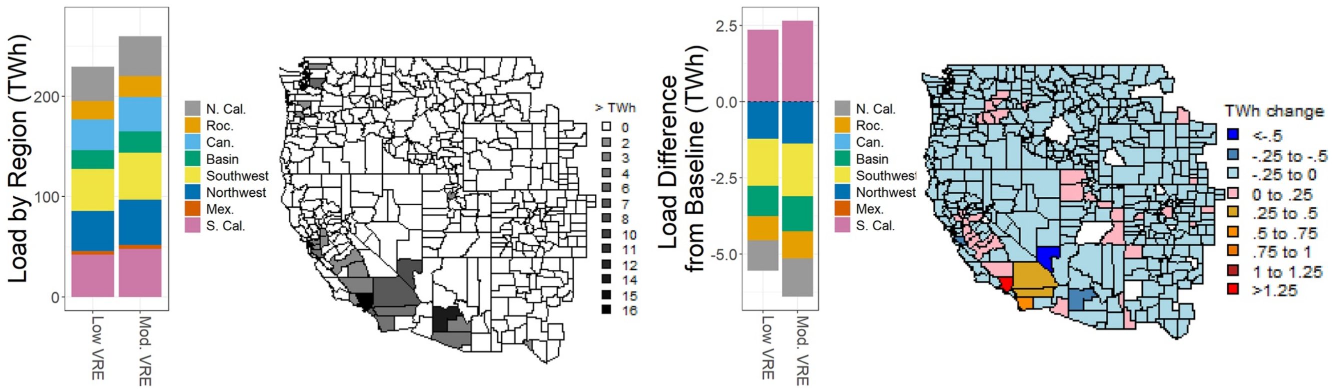

Figure 2. The TWh summer load by region (leftmost bar chart) and by county (leftmost map for low variable renewable energy (VRE)) and change in load for the extreme temperature scenario by region under extreme temperature scenario (rightmost bar chart) and by county (rightmost map for low VRE).

2.3.2. Electricity Load Adjustment for Temperature

Electricity load is sensitive to ambient temperature due to electric heating and cooling loads, primarily for space and water. Modeling this sensitivity at the power grid scale is primarily done in two ways: using top-down statistical models which relate load to ambient conditions (Auffhammer et al., 2017; FERC, 2009; Parkpoom & Harrison, 2008; Ralston Fonseca et al., 2019; Sailor, 2001; Sailor & Muñoz, 1997; Sailor & Vasireddy, 2006; Sullivan et al., 2015; Thatcher, 2007) and using bottom-up models which represent building processes by sampling from a large number of buildings (Hale et al., 2018; Taylor et al., 2019). We use a top-down approach to adjust load according to temperature based on statistical modeling of the 2005–2006 load years in the continental U.S. (Sullivan et al., 2015). Our approach uses the temperature sensitivities from Sullivan et al. (2015) as represented in the ReEDS software (Cohen et al., 2019), downscaled for this work to represent county-level and hourly responses to temperature. Figure 2 shows the summer load and change in summer load for the extreme temperature scenario. See the Supporting Information S1 for details on load modeling and additional scenarios.

In the extreme Southern California heat year, the Southern California load was 5.5% higher in June-August compared with the baseline (2.4 and 2.6 TWh increase in low VRE and moderate VRE, respectively, pink bars in second bar chart). However, the annual load for the entire Western U.S. was lower than the baseline by 1.4% because the heat wave was regionally focused and the baseline year for load (2010) was relatively warm. We note that our temperature simulation does not reflect future climate impacts, and we selected from the simulations using a grid-centric heatwave definition; therefore, the extreme temperature year we focused on does not reflect the future but provides sensitivities for grid operations with a focus on the Southern California load center.

In our analysis, we focused on the summertime months of June-August and, to highlight operation under a heat event, on the period from 7 to 14 August when the simulated temperatures created a 3-day heat spell in Southern California, causing simulated higher Southern California peak loads compared with the baseline scenario (exceeding 32 GW in the low VRE scenario and 35.5 GW in the moderate VRE scenario for 2 days).

2.3.3. Thermoelectric Power Plant Capacity Adjustment for Temperature

We estimate the derating (capacity loss) of thermoelectric power plants under heat according to major cycle type (combined cycle, combustion turbine, or steam cycle) and cooling type. We used thermal process modeling software to model the operation of coal steam and natural gas combined cycle power plants having air-cooled or evaporative cooling towers under a range of ambient conditions. From these models, we derive an estimate of the capacity loss per degree change in temperature. We relied on literature for an estimate of combustion turbine derating. We derated each power plant for temperatures exceeding the design point that we assigned for each county in order to reflect the importance of regional design criteria (e.g., locations that have higher annual temperatures are designed to operate under warmer conditions). We did not incorporate the effects of stream temperature, which would especially impact those once-through cooled power plants that use rivers or streams for cooling. Thus, once-through cooled plants are only derated according to water availability, and only if they rely on fresh surface water for cooling (Section 2.2). For details on the temperature-based derating methodology, county-level derating results, and additional scenarios, see Supporting Information S1.

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Table 2
Summary of Scenario Definitions

Scenario	Description	Adjustments Load	Adjustments Hydro	Adjustments Thermal
Base	Baseline: 2010 load, 2005 water, no deratings			
Load	Simulated temperature used to adjust load			
Air Derating	Simulated air temperature used to derate thermal			
Water	Drought reduces hydro, freshwater-dependent thermal			
Combination	Load + Air Derating + Water			

Note. Areas were shaded to show what adjustments are made in each scenario.

2.4. Heat and Drought Stress Scenarios

We studied the effects of one drought and one Southern California heat condition (i.e., stress) in isolation and combination on the two electricity infrastructures. We modeled impacts of the simulated 1977 drought year on hydropower generation and thermoelectric capacity ("Water" scenarios), the impacts of extreme heat in Southern California on electricity load ("Load" scenarios) and, separately, on thermal power plant capacity ("Derating" scenarios), and the combination of these stressors ("Combination" scenarios). Each scenario was modeled over the entire year, but we focused our analysis on the two time periods in which drought and heat are most impactful: summertime and peak week. Table 2 summarizes the stress scenarios, and Figure 3 illustrates the effects of temperature-based deratings, water-based deratings, and their combination on thermal fleet capacity. Including a "Baseline" scenario, we simulated five scenarios for each infrastructure for a total of 10 1-year, hourly simulations. Additional heat and drought scenarios are included in the Supporting Information S1.

3. Results

We evaluated the sensitivity of a low VRE infrastructure to heat, drought, and their combination and its evolution under evolving infrastructure by examining three electricity system outcomes: (a) changes in generation mix and related production cost at the system scale (Section 3.1), (b) changes in interregional transfers, which are primarily to and from Southern California (Section 3.2) and (c) changes in use of thermoelectric and hydropower fleets throughout the Western U.S. (Section 3.3).

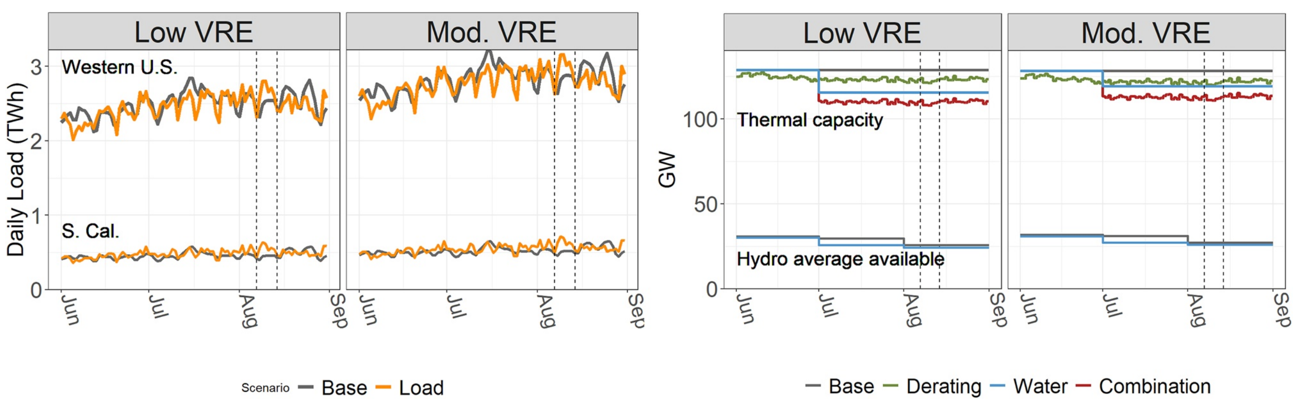

Figure 3. Left: Daily load. Right: Average monthly hydroavailability and daily thermoelectric capacity. *Note.* There are small changes in the hydrocapacity for the Moderate VRE infrastructure, so the baseline scenario is not identical to the low VRE infrastructure. Hydropower is dispatched optimally in the model within the month, so this figure represents the average available by month. Right: total of coal, gas CC, and gas CT daily capacities. The focus period of 7–14 August is outlined in dashed lines. Combination scenarios are not shown for daily load or hydro as they are the same as the Load scenario and Water scenario, respectively, in those figures.

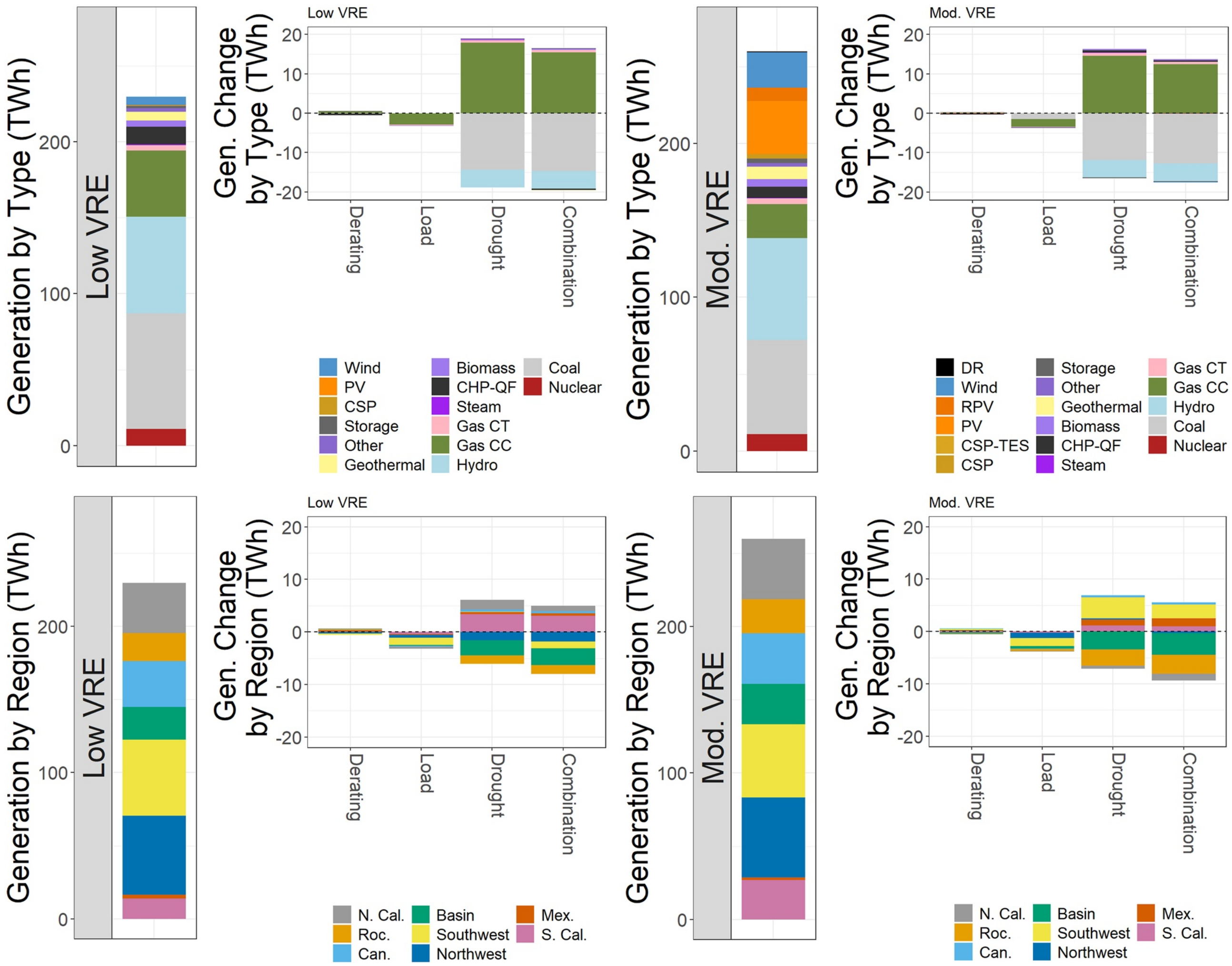

Figure 4. Total summer generation in baseline and differences in generation relative to baseline for each scenario. Generation by generator type (top) and by region (bottom) are shown. Gas CC generation increases by 15–18 TWh to compensate for drought, but regional generation changes are smaller because a region can decrease generation of one type (e.g., coal) while increasing generation of another (e.g., natural gas). *Note.* The Load scenario reduces overall load while increasing load in Southern California, as described in Section 2.

3.1. Drought Dominates Changes in Production Cost and Generation Mix at the System Scale

We examine how drought and heat, separately and together, effect the optimal dispatch of the two systems by considering the generation by type of power source ("generation mix"; Figure 4, top) and generation location (Figure 4, bottom). The drought scenario had a much larger impact on the change in the generation over the Western U.S. than our Southern California heat scenario for both infrastructures. Gas combined cycle (gas CC) compensated for the loss in hydrogeneration and coal capacity in both the high and low VRE infrastructures (Figure 4, top), and the smaller coal derating in the moderate VRE scenario required less compensation. Regionally, the drought response varies between infrastructures (Figure 4, bottom). In the low VRE infrastructure, the gas CC generation responding to drought is regionally diverse, with the largest single region being Northern California, while in the moderate VRE infrastructure, gas CC generation response is largely from the Southwest (Figure S15 in Supporting Information S1). Overall Figure 4 shows that drought changes the generation mix, infrastructure disrupts the regional response to drought, and the Southern California heat scenario has a relatively small impact on generation mix.

We use total system production cost, a system-wide metric that reflects the cost to operate including fuel costs and generator start-up costs, to explore the differences between the effects of drought and heat on the two systems (Figure 5). Changes in production cost are largest for the 1977 drought scenario (Figure 5 and Table S6 in

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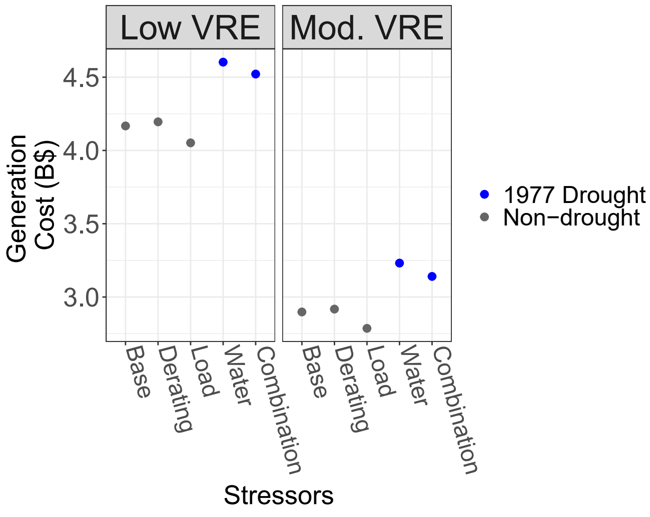

Figure 5. Summer generation (production) costs.

Supporting Information S1), reflecting the increase in gas CC generation due to drought (excepting the obvious reduction in production cost for the moderate VRE infrastructure). Temperature-based thermal deratings increase production cost less than 1%, while cost decreases in the load scenarios by 3% in the low VRE scenario and 4% in the moderate VRE scenario because the Western U.S. load decreases 1.4% overall (though load is high in Southern California). Production costs increase 10% due to drought in the low variable renewable system and 12% in the moderate variable renewable system, driven by the reduction in hydroelectric and coal generation that is replaced by natural gas. The cost increase of combination scenarios relative to the baseline is 8%, which is well approximated by adding the incremental costs of individual stressors (underestimating production cost by less 0.2% or $6M in the low VRE scenario and $1M in the moderate VRE scenario). The fact that the production cost under combination stresses is nearly "the sum of the parts" is largely because the cost is driven by the extent of the drought and because our Southern California load scenario had relatively constant load across the Western U.S. However, it is surprising because it indicates that despite changes in regional flow dynamics described later in this section, combination stressors do not drive the system past a tipping point to where marginal generation costs are significantly higher.

3.2. Average Interregional Dependence Decreases With VRE or Drought, and Increases With Heat

We considered interregional dependence—the extent to which optimal operation depends on other regions—by measuring the total of regional transfers (imports or exports between regions, which sum to zero across the entire Western U.S. simulation). Note that "Regional net imports" is the difference between a region's load and its in-region generation; energy may flow into and out of a region on various paths, but we consider any load that is higher than in-region generation to be its net import, and conversely for regional net exports. Figure 6 shows that interregional dependence was most affected by the infrastructure scenario, with the moderate VRE system relying overall 21% less on regional transfers in the summertime than the low VRE system in the baseline scenario. Most of the interregional dependence is driven by Southern California, and that region alone relied 34% less on transfers in the moderate VRE system compared with the low VRE system in the baseline scenario. Across all scenarios, total regional summertime transfers were at most 26 TWh in moderate VRE infrastructure, while in the low VRE system they were up to 32 TWh. Southern California alone imported a total of 20 TWh in the baseline moderate VRE scenario compared with over 25 TWh in the baseline low VRE scenario, despite load growth, largely because of Southern California solar generation in the moderate VRE system.

Comparing heat and drought stress impact on summer regional transfers in Figure 6, the regionally extreme Southern California heat scenario had the largest impact on regional net imports, while temperature-based deratings had the smallest impact in both the low and moderate VRE infrastructures. The hot summer in Southern California ("Load" scenario) was compensated by imports from most other regions where load decreased, so that the total regional net imports increased by 10% in the low VRE system and 12% in the moderate VRE system. Imports to Southern California alone increased 10–14% in the "Load" scenario. In the 1977 drought scenario, regions depended more on their own generation. In the low VRE system, drought caused a 9% decrease in regional transfers, while in the moderate VRE system, the effect was a 6% decrease. Imports to Southern California alone decreased 12% and 6% in the drought scenario for low and moderate VRE, respectively. The impact of temperature-based thermal deratings on regional transfers was small relative to the impact of the load, drought, and combination scenarios (changed at most 1%). Under combined heat-drought stressors, Southern California still imports to meet load but must also increase in-region generation for a moderating effect of 2% decrease in total regional transfers in both infrastructures. Imports to Southern California alone decreased 2% in the low VRE system but increased 8% in the moderate VRE system in the combination scenario. In other words, the optimal system response to Southern California heat is to expand interregional dependence, but this behavior is suppressed when heat coincides with severe droughts affecting the Western U.S.

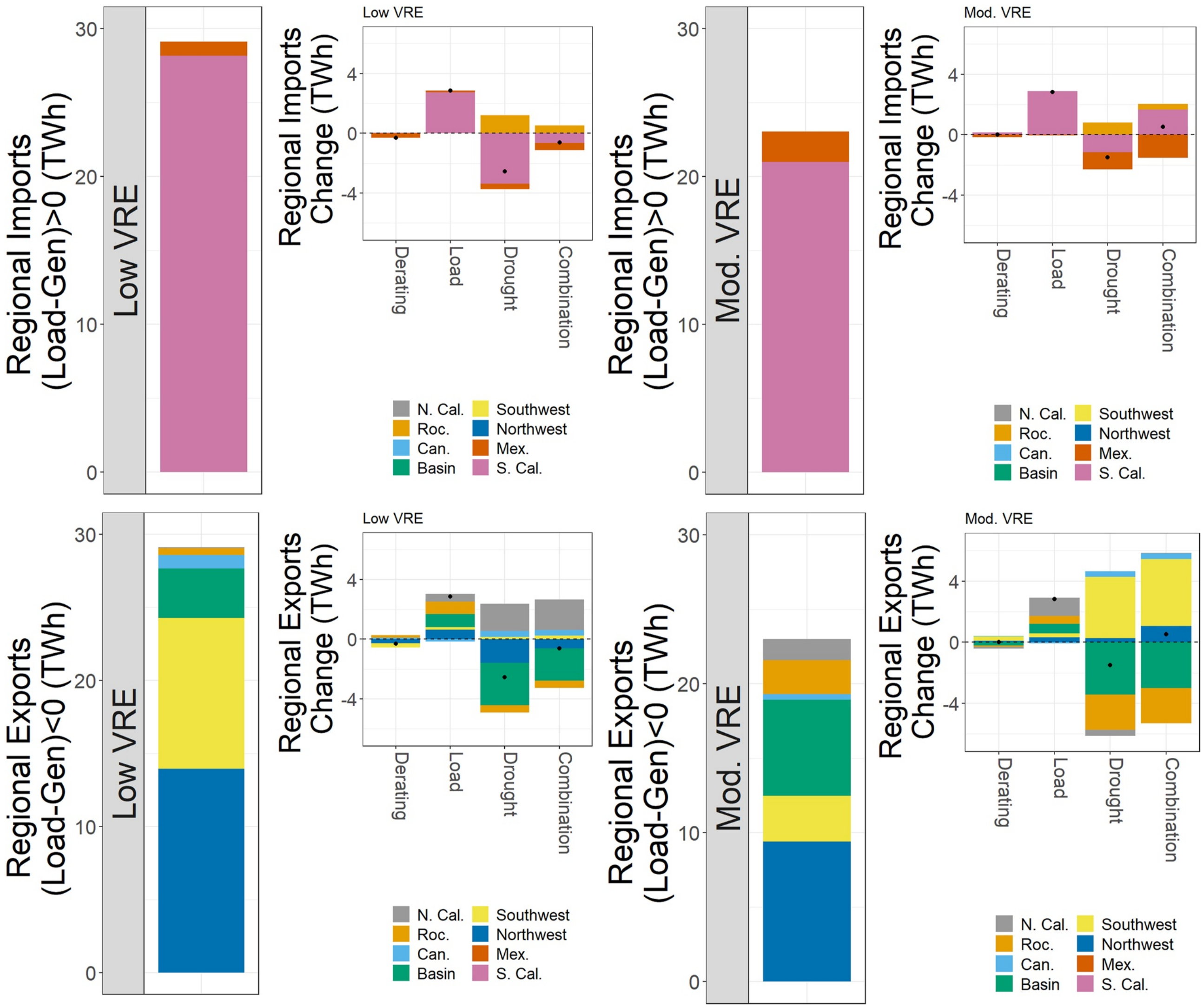

Figure 6. Regional net imports (top charts) and exports (bottom charts) in the summer in the baseline and difference from baseline in each scenario. *Dots* indicate total change in net imports or exports across all regions for clarity.

The regional generation patterns underlying these transfers are fairly straightforward in the Load scenario: Southern California imports more, and every other U.S. region compensates with exports. But drought dynamics are more nuanced. Water-based coal deratings caused exports from the Basin to decrease, caused the Rockies to become a net importer, and caused the Southwest to compensate in-region with gas CC. Hydropower impacts of the drought modeled were strongest in Northern California, where gas CC compensated for drought, especially in the low VRE system in which Northern California began to export during drought. The Northwest had nearly equal hydropower and water-based thermal losses in the drought modeled, and its role changed as infrastructure changed: in the low VRE system, Northwest exports decreased significantly in drought, while in the moderate VRE system, they were lower overall but constant through drought. The Southwest exported less in the baseline moderate VRE scenario than in the baseline low VRE scenario but became the primary compensation for regional transfers due to drought in the moderate VRE system due to its gas CC capacity. Southern California and Mexico imported less in the drought, using some available in-region thermal capacity instead, though Southern California did this to a lesser extent in the moderate VRE system because of its limited thermal capacity. See Figures S15–S19 in in Supporting Information S1 for more regional detail.

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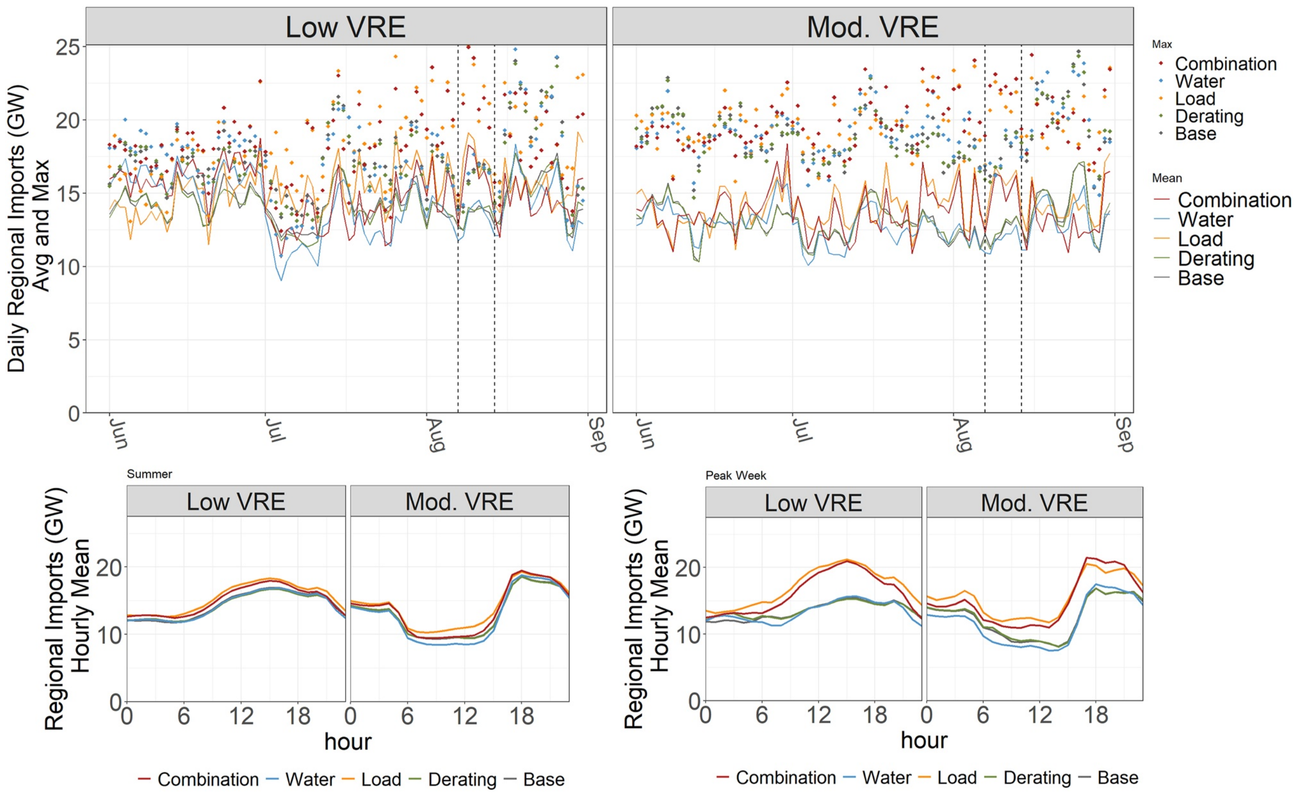

Figure 7. Mean and max daily regional net imports (total of all regions) for every day of the summer highlighting the 7–14 August focus week (top). Regional net imports averaged by hour of day over the entire summer (bottom left) and over the 7–14 August weeks (bottom right). Dots indicate maximum, and lines indicate average (daily max/average on top, or hourly average on bottom).

3.3. Peak Interregional Dependence Is Maintained Regardless of VRE Penetration and Further Increases Under Heat Events

We examined daily, hourly, and peak-period dynamics that are important for power system operations (Figure 7) and hidden in the coarse temporal resolution (summer) results. In the low VRE system (Figure 7, bottom left), regional transfers follow a typical electricity load shape, increasing steadily from morning to afternoon. The diurnal profile of the regional transfers changes in the moderate VRE system because of the significant increase in solar generation, having a sharp ramp in the afternoon to evening (reflecting the "duck curve" created by solar generation). Regional transfers increase in the peak week overall compared with the summertime average (Figure 7, bottom right). Despite the seasonal total of regional transfers being lower in the moderate VRE system than in the low VRE system (Figure 6), during the peak week, average peak hourly regional transfers are similar in the moderate and low VRE systems (20–22 GW), though the peak occurs later in the evening in the moderate VRE system. The Southern California heat stress scenario is differentiated strongly in the diurnal profiles of the peak week but not the summer average profile, showing that the increase in regional transfers due to the heat scenarios observed on the seasonal scale (Figure 6) is due largely to impacts at peak weeks (Figure 7). While the combination of heat and drought moderates total seasonal regional transfers (Figure 6), during the peak week, peak hour regional transfers in the moderate VRE scenario are higher under combined heat and drought than heat alone (Figure 7, bottom right), indicating the importance of peak regional transfers in responding to combined heat and drought events in the future.

3.4. Summertime Thermoelectric Capacity Factor Increases With Drought

Because hourly resource availability is key to robust system operations during extreme conditions, we examined the hourly simulations for the use of the flexible thermal and hydroelectric fleets to understand response to heat and drought stress. While simulations resulted in no unserved energy and reserve shortages of less than 0.01%

of reserve requirements, examining the thermal fleet use gives a measure of the robustness of the system to even more extreme conditions. First, we considered the thermal fleet capacity factor, defining the thermal capacity factor as a fraction of the total coal and gas capacity that is dispatched, accounting for any daily or seasonal deratings. The summertime thermal fleet capacity factors were 0.44 and 0.31 for low VRE and moderate VRE systems, respectively, in the baseline scenario. The load scenarios decreased the average summertime thermal fleet capacity factor by 0.01. The thermal derate scenarios increased it by 0.02. Drought had the largest single impact on the thermal fleet capacity factor, increasing it by 0.03–0.05. The combination of Southern California heat and drought increased the thermal fleet capacity factor further by up to 0.06 compared with the Base conditions, but in all hours, the fleet capacity factor remained below 0.70.

4. Discussion

4.1. Implications of Research

We built on previous research (Steinberg et al., 2020) that identified the relative importance of electricity load in a planning-scale study of the U.S., here specifically examining regional extreme heat rather than overall warming trends and confirming the importance of regional heat patterns. We studied the regional importance of the Southern California load identified by Hill et al. (2021), here specifically quantifying regional interdependence under isolated and combined heat and drought. Because both drought and regionally extreme heat impact energy transfers across the Western U.S., we emphasize the need to account for these interregional dependencies rather than isolate individual regions. The significant power outages of August 2020 in California showed that extreme heat can cause service outages in a real system and that regional imports (or lack thereof) are a factor in such events (California ISO, 2021), so modeling systems with perfect regional coordination, as we do here, highlights the benefits of regional coordination for responding to extreme events such as heat and drought. To that end, we found that simulations of a Southern California heat scenario increase the summertime regional transfers by 10–12% when there are no barriers to such coordination. While average summer regional transfers decrease 21% with relatively moderate infrastructure changes, the hourly regional transfers during *peak* periods do not decrease with infrastructure changes, so regional transfers remain important for operations. Importantly, the heat event results in the highest peak regional transfers in our simulations. Compounding these peak regional transfers is the fact that thermal fleet capacity factors are highest at peak times and are increased by the supply side heat and drought stressors.

Though different drought scenarios would change the magnitude of the cost impacts, our 1977 drought simulation fits the linear trend between Northwest and Northern California hydropower and Western U.S. production cost shown over a wide range of droughts in previous work (Voisin et al., 2020b). We also simulated another more extreme drought and the three other temperature scenarios (see Supporting Information S1) and confirmed that production cost under combined heat and drought is well approximated by the sum of the individual effects in those additional 18 simulations.

Our electricity grid simulations confirm the analysis of Miara et al. (2017), showing that the impacts of thermoelectric power plant temperature-based deratings on the grid were small in the Western U.S., and our work extends this conclusion by confirming it in a historical and future system. However, our water-based deratings did impact thermal generation significantly, and we highlight the need to further understand the water-sensitivity of thermoelectric power generation. We found that water limitations of hydroelectric generation are important not only in isolation, as is established by many (O'Connell et al., 2019; Tarroja et al., 2016, 2019; Voisin et al., 2016, 2018, 2020b), but also relative to regionally extreme heat. We show the importance of connectivity across the Western U.S. in response to heat and drought, building on Voisin et al. (2020b), which focused on connectivity of the Western U.S. under varying water availability and identified regional dependencies. Our results indicate the key stress modes (electricity load, water-limited generation constraints) where planners may consider focusing scenario development, model complexity, and associated computational power. This contribution is important as models increase in complexity and consider more significant infrastructure changes than the moderate VRE case we tested here (Cochran & Denholm, 2021; Larson et al., 2020; Phadke et al., 2020; Mai et al., 2012). For example, Cochran and Denholm (2021) compared options for the city of Los Angeles, California to meet 100% renewable energy targets using a comprehensive framework with more than a dozen different energy models including power flow, building energy demand, and capacity expansion models. While that work was comprehensive in linking scales, it used a single electricity demand load year (adjusted for projections of future monthly warming with the peak load week adjusted to reflect recently observed extremes). The fact that the study did not adjust generation for heat or drought—though perhaps less important because the study focused on an islanded Los Angeles system—limits its relevance for coordinated operations under significant extreme heat or drought events. Our work demonstrates the importance of heat and drought factors in a high-resolution power system model while a more complete treatment of hydrometeorological uncertainty is possible with new tools by Su, Kern, Denaro et al. (2020).

Research linking long-term investment changes to the operational system impacts of heat and drought stress is needed in the Western U.S. context, and this work identifies supply side water stress and demand-side temperature stress as key variables and highlights the importance of interregional dependence.

4.2. Limitations of Research

Physics-based models of electricity load for building energy demand (Hale et al., 2018; Taylor et al., 2019) may identify evolving sensitivities of the Western U.S. grid to regionally extreme heat because they can capture the effects of multiday heat events and incorporate building technology changes (e.g., air-conditioning penetration and energy efficiency). Representing multiday heat events may result in different diurnal grid stress when air-conditioning loads remain high overnight, for example, shifting the hourly interchange patterns observed in the current work. In addition, our stochastic simulations did not capture widespread heat events that would limit the ability of interregional transfer to Southern California, compared with Southern California heat wave we simulated here.

Our modeling of hydropower in the production cost model takes a moderate approach between energy-centric and water-centric methods, which has implications on the interpretation of our drought scenario results. Hydropower constraints that we pass to the production cost model at monthly resolution are consistent on a total energy basis with submonthly periods of high or low generation required by those nonenergy constraints included in the VIC-MOSART-WM models, but the true energy storage capability varies between facilities and we expect that our results overestimate the storage duration of some plants, while underestimating others. Improving reservoir storage representation using individual plant data as in Steyaert and Condon (2020) could be linked with changes to production cost models to address differing temporal horizons, however a power system model must also be formulated to include such heterogenous characteristics and this work is nontrivial (Oikonomou et al., 2022). Further, the large-scale representation of extreme events on water resources and reservoir operations is not set up for extreme events; however, higher resolution models are emerging (Steyaert & Condon, 2020; Turner et al., 2021) that would better help address extremes such as multiyear droughts that might increase the resource limitations in our simulations as hydropower is depleted. Complementary models with dynamic water demand competition for water availability (Yoon et al., 2021), when combined, could also provide insight into more severe hydropower restrictions which may result in resource constraints on daily or hourly basis not observed in our simulations.

Our electricity system simulations do not account fully for the spatial and temporal correlations that exist between hydrometeorological variables. Though our stochastic model generates simulations of precipitation and temperature that are across variables, and space-time consistent in dependencies, and hence implicitly produces included linked precipitation and temperature extremes, we choose to use historical drought for water constraints on electricity and therefore our treatments of drought and extreme heat were ultimately separate. While spatiotemporal correlations of renewable resources and load were inherently maintained by using a consistent weather year for load and wind power in the historical system base scenario (which had little solar), in all other scenarios, this type of hydrometeorological consistency was not maintained. Further, we did not include any nonstationarity in climate. These limitations mean that our scenarios do not reflect hydrometeorological correlations or climate change, but rather their utility is to demonstrate a method and uncover the grid dynamics that result from uncorrelated drought and regional heat extremes.

We did not vary wind and solar resource profiles other than to capture the changing penetration (low versus moderate VRE), but others have found that changes in renewable resources' availability have the largest impact on unserved energy (Nahmmacher et al., 2016) and operational costs (Peter, 2019) of the stressors they studied. Craig et al. (2019) found that changes in wind and solar resources due to climate changed CO_2 emissions, nuclear generation, and electricity production costs in power system operation simulations for Texas, but they did not compare these with other stressors. Bloomfield et al. (2021) found that while climate change increases uncertainty around wind and solar resource availability and electricity load, diverging infrastructure expansion pathways contribute more to uncertainty than climate. Additional wind and solar resource scenarios, historical or simulated, could change the regional interactions (by driving regional power flows to those areas experience VRE resource "droughts" or increasing VRE curtailment when VRE resources are high) and robustness of the systems (if VRE resource changes are not anticipated in planning).

Fuel price fluctuations or other conventional fuel supply side dynamics not included in our simulations could compound the heat and drought stress events we considered by driving up production costs and changing the dispatch order. For example, O'Connell (2019) found that natural gas prices interact with water availability in the operation of the Western U.S. grid.

5. Conclusion

Contemporary and hypothesized Western U.S. infrastructures with 5% and 31% variable renewable generation shares, respectively, were evaluated for their sensitivity to individual and compounded impact of a single drought scenario and a single Southern California heat wave scenario on generation and load. The use of a stochastic temperature simulation combined with spatially resolved historical drought was an important step in this toolset that could be expanded to incorporate other grid stressors in high-resolution power system models, ultimately leading to improved sensitivity analyses that are not limited by the (current) ability of climate models to capture extreme conditions. Methods demonstrated contribute to the critical research area in representing multisector dynamics using linked models or multisector models that incorporate Earth, infrastructure, and human systems to understand the main drivers and outcomes of and adaptations to change.

Through this experiment, we found that simulated Western U.S. electricity production cost and generation portfolio mix were sensitive to water stress on generation, while interregional dependence primarily supplying Southern California was sensitive to temperature stress on load and water stress on generation, for both infrastructures. The sensitivity to air temperature-based thermal deratings was small. Our simulations suggest that the Western U.S. responds to drought by using additional natural gas generation and to Southern California heat by leveraging the system's interconnectedness. Summertime average regional transfers to Southern California increased up to 14% in our Southern California heat scenario. In the baseline scenario those transfers decreased 34% in the moderate VRE system compared to the low VRE system.

Another key finding was that during peak times, regional transfers, which are highest in a heat wave over Southern California, are just as high in the moderate VRE system as in the low VRE system simulated. The 2020 California power outages were in part caused by inadequate planning for net peak demand hours (California ISO, 2021), and our simulations suggest that heat and drought combined with future increases in solar in Southern California require consideration of hourly interregional transfers and (potentially) related transmission expansion, energy storage, or market flexibility solutions. Given that the energy and water securities are often planned at the regional level, our findings consolidate others to show that regional connectedness needs to be considered to plan for extreme events, and our study highlights that this connectedness may persist under a moderately high VRE infrastructure. An important extension of this work is to explore higher VRE scenarios by linking the current framework to a capacity expansion model that can explore the uncertainty in how future infrastructures will evolve.

These novel analytics focused specifically on extreme events to investigate the need to build for extreme events rather than trends. This experiment was enabled by multisector dynamics analysis using a combination of a stochastic extreme weather generator, complex water availability modeling, and high a resolution power system model. We emphasize the importance of modeling water-based grid stress, which remains a challenge given the complexity of the evolving management of water system infrastructure, as well as extreme electricity demand scenarios, which are also the subject of research to integrate technology innovation and more controls. Finally, we also emphasize the need to use power system models that represent regional grid interactions to design and evaluate infrastructure under extreme events and to develop high-resolution power system models capable of incorporating probabilistic information for individual and compounded events for a risk-based approach to planning for extreme events.

Data Availability Statement

Simulated temperatures, monthly generation constraints on hydropower and thermoelectric generation, supporting data for thermoelectric temperature deratings, electricity load scenarios, and aggregated power system operation simulation outputs are available at https://github.com/IMMM-SFA/dyreson_etal_2021_earthsfuture.

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