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FY 2023 Fourth Quarter Performance Metric: Modeling the Impacts of Heat Waves on the U.S. West Coast

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Contents

1.0	Proc	luct Definition	1
2.0	Product Documentation		1
	2.1	Global-Scale Scenarios	2
	2.2	National-Scale Modeling	3
	2.3	Regional-to-Local-Scale Modeling	3
3.0	Results		4
	3.1	Temperature during the July 2018 Heat Wave and its Future Analogs	4
	3.2	Heat Wave Impacts on Electricity Loads	6
	3.3	Heat Wave Impacts on Solar and Wind Generation	7
	3.4	Heat Wave Impacts on Electricity Grid Stress	7
4.0	Refe	erences	.10

Figures

Figure 1. The integrated modeling framework for heat wave impacts on the U.S. western electricity grid	.2
Figure 2. Balancing authorities in the Western Interconnection	.4
Figure 3. Population-weighted maximum daily temperatures during June, July, and August in the Western Interconnection of the U.S. for 2018 and over the historical period 1980-2019	5
Figure 4. Hourly population-weighted temperatures and hourly electricity loads for CISO and LDWP in 2018, 2058, and 2098.	6
Figure 5. Simulated solar and wind generation in CISO and WAPA, Desert Southwest during the July heat wave	.7
Figure 6. Simulated average hourly LMPs and total hourly unserved load in the Western Interconnection for the July heat wave.	8
Figure 7. Simulated average hourly LMPs and total hourly unserved load in CISO for the July heat wave.	.9
Figure 8. Simulated average hourly LMPs and total hourly unserved load in AZPS for the July heat wave.	.9

1.0 Product Definition

The first three 2023 quarterly reports focused on the U.S. Department of Energy (USDOE) capability to simulate and understand atmospheric rivers and their impacts through the development of the Energy Exascale Earth System Model (E3SM), in conjunction with novel model evaluation and analysis methods. In this fourth quarter report, the focus is on USDOE advances in using a hierarchy of models to simulate and understand the impacts of heat waves on the U.S. West Coast.

It is well documented that heat waves are becoming more severe and more frequent¹ and pose risks to human and natural systems, including severe health impacts such as mortality and morbidity due to heat stress in urban heat islands;² electric grid outages due to the compounding impacts of increased demand and/or negative impacts of heat on infrastructure;³ earlier snowmelt reducing reservoir storage;⁴ excess water temperatures affecting power plant cooling and ecosystems;⁵ reduced agricultural yields due to lower soil moisture and plant mortality;⁶ and wildfire risks due to reduced fuel moisture content.⁷ Increasingly severe heat waves affecting the western U.S. have been of particular concern.^{8,9,10}

USDOE investments in modeling human-Earth system interactions are increasing our capability to model and better understand the cascading multisectoral and multiscale impacts of heat waves. This fourth 2023 quarterly report documents modeling advances to understand how heat waves affect the electricity grid in the western U.S. In addition to increasing electricity demands through increased use of air conditioning, heat waves can negatively affect generation from renewable resources such as wind, solar, and hydropower, ^{11,12,13} reduce the efficiency of thermoelectric generation, and cause failure of transmission lines.¹⁴ These compounding impacts negatively affect the ability of grid operators to balance supply and demand. As demands increase and/or the most-cost-effective generation resources are compromised, the costs of operating the electricity grid increase. In the worst case, power outages (also called "unserved energy" or "loss of load") occur.^{15,16} Traditionally, electricity grid planning has relied on historical, stationary conditions to guide investment and long-range planning decisions to forecast demand and study grid resiliency under extreme events.^{17,18,19} With climate change impacts becoming increasingly severe, USDOE foundational science research is informed by the societal need for open-source, integrated human-Earth system modeling capabilities that address climate non-stationarity and can simulate the full range of demand and supply impacts that can occur during heat waves.²⁰

This report provides clear evidence of USDOE advancements in simulating the impacts of heat waves on the western U.S. electricity grid. This research has developed the first completely open-source, validated, and integrated hierarchy of models for this purpose. Using these tools, we can link future climate projections to models of national-to-global energy economy interactions, electricity demands, power plant siting, renewable resource generation, and grid operations.

2.0 Product Documentation

As shown in Figure 1, we use a hierarchy of open-source, integrated human-Earth systems models to simulate heat wave impacts on the electricity grid of the western U.S. This modeling framework is unique in its ability to maintain internal consistency in climate and socioeconomic assumptions, while also increasing spatiotemporal and process resolution, from global to local scales. All the models and data used in this framework are open source, and all the models were developed for USDOE. We use this

framework to simulate the impacts on electricity demands, solar and wind resources, and electricity system grid stress during a significant July 2018 heat wave that affected most of the western U.S.²¹ This heat wave produced record temperatures, requests from the major electric grid operator in California for power conservation, and electricity outages in Arizona due to temporary power shortages.²² We also simulate the impacts of two future heat waves that represent how the July 2018 heat wave would replay after 40 and 80 years of additional warming (in 2058 and 2098, respectively) to understand future grid stress. To isolate and understand the effect of the future, more extreme heat waves, we assume that 2018 electricity infrastructure and population remain fixed.

We provide summaries of each component of the framework below along with references providing more detailed information on each model and data set.



Figure 1. The integrated modeling framework for heat wave impacts on the U.S. western electricity grid.

2.1 Global-Scale Scenarios

The modeling hierarchy uses global climate and socioeconomic scenarios based on the most recent data sets and assumptions used in the climate science community: the Coupled Model Intercomparison Project, Phase 6 (CMIP6)²³ and the Shared Socioeconomic Pathway (SSP)–Representative Concentration Pathway (RCP) SSP-RCP framework.²⁴ For the results presented in this fourth 2023 quarterly report, we focus on an RCP8.5 climate scenario (a very warm future climate driven by high greenhouse gas emissions consistent with the SSP5 socioeconomic scenario) so that we can investigate how future heat waves in such a climate could affect electricity demands, renewable resources, and electricity grid operations.

2.2 National-Scale Modeling

The national-scale modeling approach has two primary components. First, we use a thermodynamic global warming (TGW) approach to simulate future climate on an hourly basis for the contiguous U.S. over the 21st century at 1/8th degree spatial resolution.²⁵ The simulations replay the weather events of a 40-year historical period (1980-2019) under different levels of warming determined from an analysis of the CMIP6 archive ("hotter" versus "cooler" models) to produce future climate over the period 2020-2099. This storyline, or analog, approach allows us to explore how past extreme events, such as heat waves, could play out under a warmer future. Each event re-occurs twice in the future simulations, first with 40 years of future warming and then with 80 years of future warming. These simulations provide high spatiotemporal and process resolution and physical consistency across climate variables over the U.S. for the entire 21st century.

The national-scale modeling also includes a simulation of 21st-century climate-energy-water-landeconomy interactions using version 5.3 of the Global Change Analysis Model, with additional detail in the U.S. (GCAM-USA)²⁶. GCAM-USA provides internally consistent future scenarios of energy prices and quantities, water consumption, and land use and land cover change for the U.S. and the rest of the world on a five-year time step. The model uses the SSP assumptions regarding population, including state-level projections for the U.S.,²⁷ and GDP change as key inputs to its simulation of future demands. In addition, we use the TGW simulations to model the impact of future climate on annual building electricity demands, water availability, and agricultural yields and apply those as inputs to GCAM-USA.

2.3 Regional-to-Local-Scale Modeling

The modeling at the regional-to-local scale includes climate and population impacts on hourly electricity loads ("loads" is the term typically used instead of "demands" in grid operations modeling, so we will adopt it for the rest of this report), power plant siting, renewable resource generation, and electricity system grid operations. The electricity grid operations model takes the hourly loads and renewable resource information as inputs and then determines how the grid would operate and if grid stress occurs (i.e., high operating costs or outages). The local-scale modeling maintains internal consistency with the global and national-scale modeling because it uses the same climate and socioeconomic data and assumptions and the state-scale economic and energy system outcomes from the GCAM-USA simulation are used as boundary conditions.

The Total ELectricity Loads (TELL) model is a machine learning (ML)-based approach based on historical hourly weather and electricity loads. TELL uses population weighting of weather data because weather-driven electricity loads will only occur where people are located. TELL aggregates gridded 1-km population data to the county scale and weights county-scale hourly weather variables that have been derived from the 12-km TGW resolution.²⁸ TELL combines its ML models with GCAM-USA projections of state-scale annual electricity demand and future hourly climate to produce projections of future hourly loads at the Balancing Authority (BA) scale.²⁹ BAs are the organizations within the U.S. electricity grid that balance supply and loads. The U.S. has three major interconnections (Western, Eastern, and the Electricity Reliability Council of Texas [ERCOT]) that operate independently, each with its own BAs. Figure 2 shows a map of the 28 BAs in the Western Interconnection that are the focus of this quarterly report.



Figure 2. Balancing authorities in the Western Interconnection.

The Capacity Expansion Regional Feasibility (CERF) model provides a means to translate the GCAM-USA state-level electricity system expansion (and retirements) to on-the-ground infrastructure within each BA at a 1-km² resolution. The model combines geospatially defined siting policies, other land- and water-based constraints specific to each type of generating technology, interconnection costs, and the economic value of new electricity generation in each BA.³⁰ We combine CERF renewable power siting locations with solar and wind plant configurations³¹ and the TGW climate data in the Renewable Energy Potential (reV) model³² to determine hourly solar and wind generation.

The Grid Operations model for the Western Interconnection (GO-WEST) is a production cost model that determines how to operate generation to meet load within each BA while minimizing annual operating costs for the overall interconnection. GO-WEST ingests the results of TELL, CERF, and reV and then simulates the hourly balancing of supply and load in each node within its BAs over the course of a year.³³ GO-WEST is designed with a flexible resolution to simulate operational risks due to weather extremes while balancing model accuracy and run time. Key metrics of grid stress produced by GO include hourly locational marginal prices (LMPs, \$/MWh) and hourly unserved load (MW).

3.0 Results

3.1 Temperature during the July 2018 Heat Wave and its Future Analogs

Figure 3 illustrates the population-weighted maximum daily temperatures calculated from the TGW data for the western U.S. during the summer of 2018 (June-August) with a comparison to the temperatures during 1980-2019 and the daily mean over that period. July 2018 temperatures exceed the 42-year mean in all but three days of the month. Two distinct periods of high heat occur in July, early and

late in the month. For this analysis, we focus on the later July heat wave (July 22-28; red shading in Figure 3) period because it affected a larger part of the western U.S.



Figure 3. Population-weighted maximum daily temperatures during June, July, and August in the Western Interconnection of the U.S. for 2018 and over the historical period 1980-2019.

In the top panels of Figure 4 we show examples of the population-weighted hourly temperatures at the BA-scale (for the California Independent System Operator [CISO] and the Los Angeles Department of Water and Power [LDWP]) during the July 22-28 heat wave for 2018 and the two future analogs, 2058 and 2098, under the RCP8.5 climate scenario. Hourly temperatures are clearly higher in every hour in both BAs as the climate warms. The peak temperature in CISO during the 2018 heat wave was 94.8°F, increasing to 99.3°F and 106.5°F in 2058 and 2098, respectively. On a relative basis, the future warming caused peak temperature increases of 5% and 12% for 2058 and 2098, respectively. For LDWP, the temperature maxima and increases are somewhat smaller (94°F, 98.3°F, and 104.1°F in 2018, 2058, and 2098, respectively), likely reflecting coastal influences that moderate temperature extremes.



Figure 4. Hourly population-weighted temperatures and hourly electricity loads for CISO and LDWP in 2018, 2058, and 2098.

3.2 Heat Wave Impacts on Electricity Loads

Based on these population-weighted temperatures as well as the annual total load by state from GCAM-USA, TELL determines the hourly electricity loads for each BA in the western U.S. during the entire year of 2018 as well as for its two future analogs in 2058 and 2098. The figures in the bottom panels of Figure 4 show these results during the heat wave period for CISO and LDWP. For example, peak load in CISO in 2018 was 49,123 MW, and this increases to 50,612 MW and 51,058 MW in 2058 and 2098, respectively. The percent increases in peak load are 3% and 4%, respectively. Note that these percent increases in peak load are less than CISO's temperature increases (5% and 12%), reflecting a non-linear relationship between load and temperature increases as simulated by TELL. We observe this in other BAs as well. Further investigation is needed, but it is likely that this is caused by air conditioning equipment reaching its maximum cooling capabilities beyond certain extremes of temperature.

3.3 Heat Wave Impacts on Solar and Wind Generation

As described in Section 2.3, our electricity grid stress modeling also includes the effects of the heat wave on solar and wind generation on each plant in the region. The map on the left-hand side of Figure 5 shows the locations of solar and wind farms in the Western Interconnection. On the right of the figure, we show total hourly solar and wind generation during the heat wave periods in 2018, 2058, and 2098 within two BAs: CISO and the Western Area Power Administration (WAPA), Desert Southwest. These BAs are chosen as examples because both have solar and wind resources in the southwestern region where temperatures were highest during the heat wave. The solar and wind generation plots indicate nighttime hours so that the contrasting diurnal cycles of solar and wind generation are more apparent. The results in Figure 5 demonstrate that increased temperatures in 2058 and 2098 correspond to reductions in wind generation but have little impact on solar generation.



Figure 5. Simulated solar and wind generation in CISO and WAPA, Desert Southwest during the July heat wave.

3.4 Heat Wave Impacts on Electricity Grid Stress

As described in Section 2.3, the GO-WEST model simulates the operation of the electricity grid in the western U.S. on an hourly basis for a full year. The model incorporates the heat wave impacts on loads and solar and wind generation described in the Sections 3.2 and 3.3. To identify grid stress, we examine hourly LMPs and unserved loads during the heat wave. Increasing LMPs means the costs of meeting electricity demand are increasing. If loads cannot be met in any hour (i.e., outages occur), the model assigns a maximum LMP value of \$2,000/MWh (i.e., value of lost load), and determines the amount of unserved load. Figure 6 shows the GO-WEST model's results for average hourly LMPs (weighted by the relative load in each BA) and total hourly unserved load for the western U.S. during the 2018, 2058, and

2098 heat waves. We see that LMPs and unserved load increase in most hours across the warming scenarios. The peak hour LMP increased from \$263/MWh in 2018 to \$508/MWh (a 93% increase) in 2058 and to \$523/MWh (a 99% increase) in 2098. The mean LMP in 2018 was \$126/MWh, increasing to \$167/MWh (a 32% increase) and \$183/MWh (a 45% increase) in 2058 and 2098, respectively. Total unserved energy during the week of the heat wave increased by 72.1% from 2018 to 2058, and by 114.8% between 2018 and 2098. These large increases indicate the compounding, non-linear impacts of future heat waves on the electricity grid—assuming infrastructure remains unchanged.



Figure 6. Simulated average hourly LMPs and total hourly unserved load in the Western Interconnection for the July heat wave.

Since the interconnection-scale results reflect the transmission system that allows power flows between the BAs, they can mask even greater extremes of grid stress that may occur within individual BAs. Grid stress within a BA can lead to emergency conservation measures and planned or unexpected electricity system outages. We know from the media reports described in Section 2 of this report that CISO urged people to reduce energy use on July 24th and 25th in 2018. Figure 7 shows the average hourly LMPs and hourly unserved load simulated by GO-WEST in CISO during the 2018, 2058, and 2098 heat wave events. While the LMPs indicate some system stress during July 24 and 25 in 2018, they significantly increase on those days during the 2058 and 2098 heat waves. Note that on a percentage basis, even though the peak loads in CISO increased by just 3% and 4% in 2058 and 2098, respectively (Section 3.2), the peak LMPs went up by over 400% in both future scenarios. This reflects the need to operate much more expensive power plants to meet the load increases. There was no unserved load at any time during the week.

October 2023 DOE/SC-CM-23-004



Figure 7. Simulated average hourly LMPs and total hourly unserved load in CISO for the July heat wave.

In contrast to CISO's ability to avoid unserved load during the heat wave, various outages were reported in Arizona. The GO-WEST simulation for the Arizona Public Service Company (AZPS) BA shows that maximum LMPs were reached (\$2,000/MWh) and unserved load occurred on most days of the heat wave in 2018, 2058, and 2098 (Figure 8). Total unserved load in AZPS increased by 275% due to the 2058 heat wave and by 245% due to the 2098 heat wave with respect to the 2018 heat wave. The simulated unserved load in AZPS as a percent of total load in the BA during the heat wave was 0.54% in 2018, 1.91% in 2058, and 1.79% in 2098.



Figure 8. Simulated average hourly LMPs and total hourly unserved load in AZPS for the July heat wave.

In summary, this analysis shows that USDOE modeling successfully reproduced the impacts of a recent (2018) heat wave in the western U.S. that increased loads and reduced wind generation, resulting in higher overall operating costs and stressing the ability of grid operators to meet loads. We also show that if this type of heat wave were to re-occur with the type of warming projected by our RCP8.5 climate scenario, average regional operating costs in the peak hour could double, while certain sub-regions could experience significant amounts of unserved load.

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