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Thermal power generation is disadvantaged in a warming world

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Abstract

Thermal power plants use fossil fuels or nuclear material to generate most of the world's electricity. On hot days, when electricity demand peaks, the ambient air and water used to cool these plants can become too warm, forcing operators to curtail electricity output. Using all available observed daily-scale plant outage data, we estimate the observed dependence of thermal plant curtailment on temperature and runoff and use this relationship to quantify curtailments due to global warming. Climate change to date has increased average thermal power plant curtailment in nuclear, coal, oil, and natural gas fired plants by 0.75–1 percentage points; with each degree Celsius of additional warming, we project curtailment to increase by 0.8–1.2 percentage points during peak demand, requiring an additional 18–27 GW of capacity, or 40–60 additional average-sized power plants, to offset this global power loss. Relative to policy scenarios with global transitions to renewable portfolios or that allow aging plants to retire, thermal power generation is a systemically disadvantaged means of electricity production in a warming world. Our results point to the crucial need for additional operational data across a diversity of thermal power plants to better constrain the risks warming poses to our electricity supply.

1. Introduction

Humanity must urgently convert energy systems away from fossil fuels to reduce greenhouse gas emissions [1–3]. Nonetheless, the majority of global electricity is still produced by combusting coal, natural gas, and oil, or generated using nuclear fuel [1]. In the U.S. in 2018, for example, 83% of electricity was generated using thermal technologies (primarily natural gas, coal, and nuclear) [4]. Furthermore, substantial numbers of new fossil-fuel electricity generating facilities are planned or under construction in many rapidly growing nations [5]. This thermal generating infrastructure will likely exist for decades [6, 7], driving additional climate change, while also providing the energy people need to be resilient to climate impacts. But how vulnerable is thermal electricity production *itself* to global warming?

Thermal power plants are reliant on air and water to function: these plants use a fuel source (e.g. fossil fuels, nuclear material) to generate steam to drive an electric generator. In doing so, plants produce large amounts of heat that must be dissipated through air- or water-based cooling systems. There are three primary cooling system types: (a) once-through cooling systems, where water is drawn through the cooling system and then ejected into a river or stream; (b) recirculating water cooling systems; and (c) dry cooling systems, which do not use water. While these systems are operationally distinct, they all become less efficient at higher ambient temperatures. When ambient air or water temperatures are warm or when water availability is low [8], thermal power plants must curtail their electricity output or shutdown due to their inability to dissipate heat fast enough. Additionally, local regulations limiting thermal pollution—often meaning the temperature of rejected cooling water—can force curtailment, although plants may request thermal waivers to allow continued operation during

droughts or heat waves [9]. However, heat-related curtailment still occurs, and it is most likely on the hottest days of the year, when electricity demand is highest and when demand is expected to grow most in the future due largely to expanding air conditioning usage [10–13]. Recent heat waves have reduced power generation capacity in Europe [14, 15], and a hotter and drier future may make such curtailment events more common, creating an imperative to compensate for the resulting reduced electricity generation.

Prior work has highlighted the potential vulnerability of thermal and hydroelectric power generation to climate change [5, 15–21]. These studies use combinations of climate, hydrological, and energy system models to make their claims. However, such model-derived results are difficult to replicate and evaluate against real-world plant performance. At the same time, observational data of daily-scale plant operations is limited—particularly across a diversity of power plant and cooling types—making much needed empirical models a challenge to estimate.

Despite these challenges, there are some observations of daily-scale thermal power plant outages available for nuclear plants in the United States (U.S.) and coal, gas, and oil plants in the European Union (E.U.). Using these data, we are able to gain some important insights about the real-world sensitivity of plant capacity to extreme heat. Here we compile all available daily-scale thermal power plant-level curtailment data from the U.S. and E.U. and combine those data with historical daily-scale temperature and monthly-scale runoff to provide the first observational evaluation of the sensitivity of thermal power plant capacity to heat and water availability. We explicitly control for plant characteristics including age, fuel type, and cooling system, and implicitly for location, background climate, and local regulations. Finally, we merge our observational model with projections of future electricity generation infrastructure growth forecasts to assess the cumulative effects of curtailment over time in a warming world. Our results are the first to link observed climate impacts on the electricity sector to both energy and climate policy targets, demonstrating the pattern of risk of a continued reliance on fossil-fueled power: more warming, more electricity demand, and more generation curtailment.

2. Data and methods

We combine temperature and runoff data with daily-scale power plant outage data and electricity demand data to estimate the relationships between climate, electricity generation, and electricity demand. We limit our analysis to two summer months—July and August—as these are generally the hottest (and often driest) months of the year and outages occurring during these months are likely to be unplanned. Centering our analysis on July and August also allows us to

leverage the fact that during these months electricity demand is highest and power plant outages are lowest, meaning that outages that do occur are less likely to be due to scheduled maintenance and more likely to be due to plant overheating.

2.1. Temperature
Daily maximum temperatures from ERA-Interim [22], CPC [23], and the NCEP II Reanalysis [24] are obtained for every plant location to model curtailment. To model subgrid-scale electricity demand, these temperature data are averaged over each electricity subgrid region. Electricity subgrid regions are defined as all states which are entirely or mostly covered by a subgrid, as specified by the U.S. Energy Information Administration (EIA) [25], and defined in Section 2.3 'Electricity demand.' When estimating curtailment and demand, we average the three observed temperature datasets to create a best estimate of the daily maximum temperature. The mean correlation between the three daily temperature datasets across all nuclear power plant locations is 0.96 or above.

2.2. Runoff
Daily scale runoff data come from the Global Runoff Data Centre (GRDC), which cover the years 2007 through 2018 [26] at the majority of runoff gauges. Runoff stations are selected based on whether they fall within the same hydrologic basins as the power plants (based on the Simulated Topological Network-30p [27]). Runoff observations are available for 49% of days across all plants for which outage and temperature data are available. Despite the missing data, runoff is a significant predictor of power plant outages (see Section 2.8 'Curtailment estimation' below). The best-fit distribution for each runoff station is identified by calculating the sum of squared errors (SSEs) after fitting each of 88 standard statistical distributions and selecting the distribution with the lowest SSE (see SI table 1 (available online at stacks.iop.org/ERL/16/024043/mmedia) for a list of best distributions for each runoff station). All runoff data are smoothed using a 30-day moving average to give an estimate of monthly-scale water availability. Runoff anomalies for each station are calculated for July and August by subtracting the July–August mean runoff from each daily July–August value and dividing by the July–August standard deviation as calculated using the best-fit distribution for the station. Runoff data is used to enable comparison with CMIP5 model projections.

2.3. Electricity demand
Hourly scale electricity demand data covering 2015–2018 is provided by the EIA for the following U.S. subgrid operators: Electric Reliability Council of Texas (ERCO; covers most of TX), Independent System Operator New England (ISNE; covers CT,

RI, MA, NH, VT, and ME), New York Independent System Operator (NYIS; covers NY), PJM Interconnection (PJM; covers OH, PA, NJ, MD, DC, VA, WV, and a small part of IN), Southwest Power Pool (SWPP covers OK, KS, NE, SD, parts of ND, and a small part of northern TX), and California Independent System Operator (CISO; covers most of CA) [25]. We only analyze demand data from the U.S., but prior work has found similar demand–temperature relationships in the E.U. [13].

2.4. Electricity outages
Daily-scale outage data for 61 U.S. nuclear power stations from 2007 to 2018 is provided by the EIA (EIA-860; average plant capacity available on each day). Data describing outage events for 52 E.U. thermal power plants between 2015 and 2018 is obtained from the European Network of Transmission System Operators for Electricity (ENTSOE) and is merged with the U.S. outage data [28].

2.5. Climate models
Projections of daily maximum temperature (tasmax), daily minimum temperature (tasmin), and monthly total runoff (mrro) from 15 CMIP5 models are used. All models use the *r1i1p1* ensemble member, are run under RCP 4.5 (strong mitigation, shown in figure 4) and RCP 8.5 (worst case, shown in SI figure 1), and cover 1981–2100. A list of models is shown in SI table 2.

2.6. Global power plant data
We use power plant fuel type, capacity, and locations provided in the Global Power Plant Database by the World Resources Institute [29].

Using the available observational data and a multivariate regression analysis, we estimate the sensitivity of electricity demand to temperature for the U.S. subgrids, as well as the sensitivity of electricity curtailment to temperature and runoff at available U.S. and E.U. power plant sites.

2.7. Demand estimation
The shape of the seasonal cycle of electricity demand depends on income, air conditioner market penetration, the use of electric heating, and atmospheric temperatures [11]; in tropical climates or locations with less air conditioning, these cycles would likely be dampened, and they are reversed in the southern hemisphere.

Demand anomalies are calculated for each U.S. subgrid by subtracting the mean demand over the dataset from each daily value. These demand anomalies are then normalized for each subgrid, allowing for comparisons between subgrids of different sizes and in different climates. Daily maximum temperatures from ERA-Interim, CPC, and the NCEP II Reanalysis are averaged over each subgrid region. Then the three observed temperature datasets are

averaged to create a best estimate of the regional daily maximum temperature. Finally, the dependence of electricity demand on temperature presented in figure 1(D) is modeled using a 2nd order nonlinear regression defined as:

$$\dot{D} \sim \beta_0 + \beta_1 T + \beta_2 T^2 + \epsilon$$

where T is the best-estimate daily maximum temperature averaged over each subgrid and $\dot{D}$ is the predicted demand. This model form was selected as the simplest nonlinear form, given the known nonlinear relationship between temperature and electricity demand [11, 12]. The model R^2 is 0.56. Both the linear and quadratic temperature terms are significant ($p < 0.001$). This model captures the temperature dependence of electricity demand due to both the intensive (existing air conditioners being used more) and extensive (more air conditioners being purchased) margins [11].

2.8. Curtailment estimation
Daily plant operating capacity is calculated by subtracting the outage from the maximum plant capacity and dividing by that maximum capacity. All daily outages during the months of July and August are included, when electricity demand is high and plants are operating at near full capacity (figure 1(E)). During the summer, it is more likely that an outage will be climate-related than during other parts of the year, when more outages are planned. Each power plant is linked with a best-estimate observationally-based daily maximum temperature time series at the grid cell nearest to the plant location. Each power plant is matched with the GRDC runoff station closest to the plant that also falls in the same hydrological basin as the plant as defined by the STN-30p basin extent dataset [27]. July–August runoff anomaly time series are calculated for each selected runoff station as described above in Section 2.2 'Runoff data'. Time series for each plant are restricted to days when outage data, temperature data, and runoff data are available. Daily plant capacities are nonlinearly regressed against daily maximum temperatures and daily runoff anomalies using the following model:

$$\dot{PC}_i \sim \beta_0 + \beta_i + \beta_t + \beta_{age} + \beta_{cool} + \beta_{fuel} + \beta_1 T_i + \beta_2 Q_i + \beta_3 T_i^2 + \beta_4 Q_i^2 + \varepsilon$$

where $\dot{PC}_i$ is the estimated plant capacity at each plant, β_i is a plant fixed effect, β_t is a time fixed effect, β_{age} is a fixed effect categorizing plant construction year (before 1980, 1980–1989, or after 1990), β_{cool} is a fixed effect specifying plant cooling system type (once-through or recirculating), β_{fuel} is a fixed effect specifying the plant's fuel type (nuclear, gas, coal, or oil), T_i is the daily maximum temperature at each plant, and Q_i is the standardized daily runoff anomaly at each plant. The plant fixed effect accounts
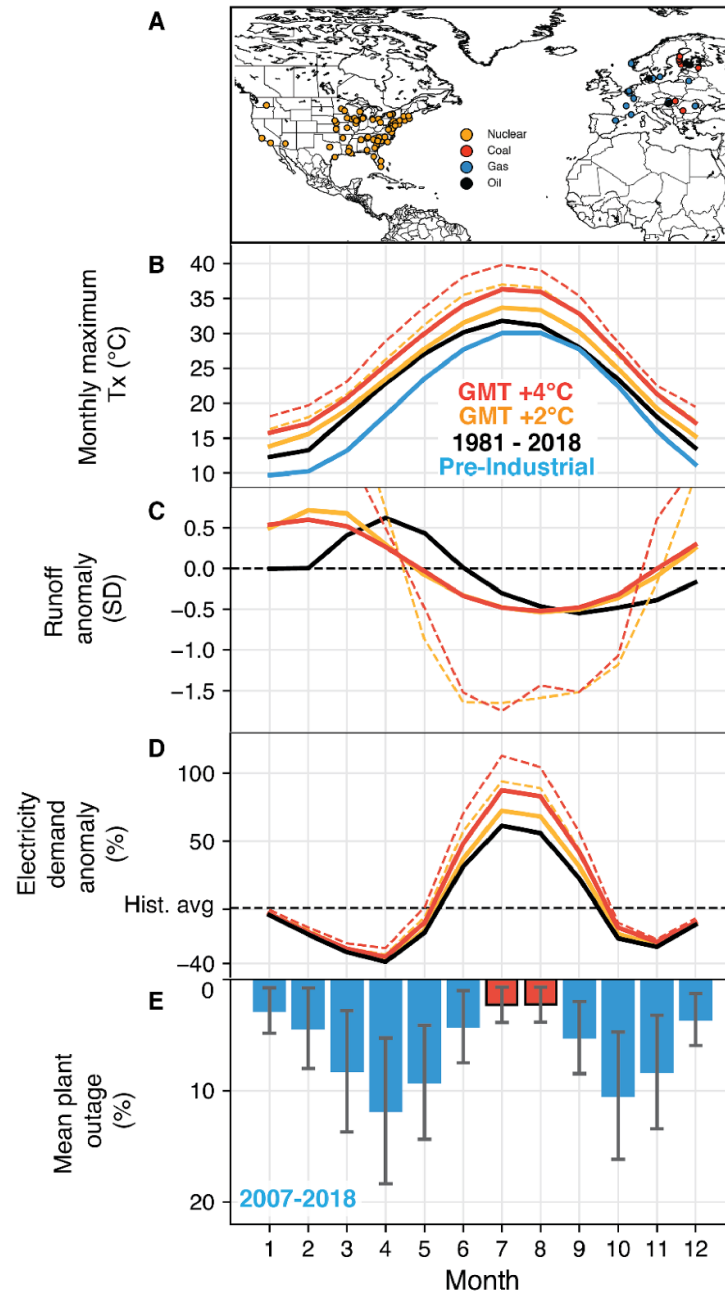
Figure 1. Climate and the electricity sector. (A) Power stations in the U.S. and the E.U. providing daily outage data. (B) Monthly maximum temperature over the pre-industrial period (1850–1900, blue), in 1981–2018 (black) and projected under 2 °C (orange) and 4 °C (red) warming scenarios. (C) Monthly mean runoff anomaly (in standard deviation (SD) from the historical mean, based on the best-fit distribution for each runoff station, see Data and methods) over 1981–2018 (black) and projected under 2 °C (orange) and 4 °C (red) warming scenarios. (D) Monthly maximum electricity demand over 1981–2018 (black line) and projected under 2 °C (orange) and 4 °C (red) warming scenarios. (E) Mean power plant outage by month, as a percentage of total plant capacity. Error bars show one SD across all plants (see Data and methods). Red bars indicate months of the year used in our analysis. In (B)–(D), solid orange and red lines show the multi-model mean, and dashed lines show the highest (warmest or driest) model from the CMIP5.

for variations in maximum generating capacity, geographic location, baseline climate, operating procedures, and environmental policy, all of which may affect the relationship between plant capacity, temperature, and runoff. All model terms are significant ($p \leqslant 0.01$), and regression coefficients and statistics are presented in SI table 3.

This nonlinear model form was selected on both theoretical and empirical grounds. First, the

efficiency of water-based cooling systems is expected to respond nonlinearly to temperature [30] due to the nonlinear dependence of evaporation rate on temperature. Second, the average adjusted R^2 (across 1000 bootstrapped models) of this model form is 0.077, indicating that about 7.7% of daily variability in plant capacity can be accounted for by temperature and runoff variability during July and August. A model including only linear temperature and runoff

variables had an average adjusted R^2 of 0.073, suggesting that the quadratic model is more appropriate. Interaction terms were not included in the model as they did not substantially change the model behavior or adjusted R^2 (0.078) but do make interpretation of the model coefficients more complex. Data on which the model is trained is presented in SI figure 6.

2.9. Curtailment projections

We use our empirically estimated curtailment model to project global generation curtailment for different levels of plant-specific warming using a four-fold strategy: firstly, we bias-correct the climate model data as described below; secondly, we estimate the across-model distribution of daily temperatures and corresponding monthly mean runoff values at plant sites as a function of global mean warming; thirdly, we estimate plant-level outages as a function of global mean warming using our curtailment model and the daily plant-level temperatures and monthly runoff values from each climate model; and finally, to propagate curtailments from the U.S.–E.U. scale to the global-scale over the coming century, we incorporate several scenarios of global energy system change to assess how varying energy technology portfolios affect global-scale electricity production curtailment with warming.

2.10. CMIP5 bias correction

To account for systematic temperature biases in the CMIP5 models, we apply a decile-matching bias correction procedure [31] at each power plant location. First, we compute the mean temperature in each decile of the historical temperature distribution at each power plant in both the best-estimate observationally based temperature dataset (described above in Section 2.7 'Demand estimation') and in each CMIP5 model. Next, the bias correction is computed as:

$$C_{d,m} = \overline{T_{d,o}} - \overline{T_{d,m}}$$

where $C_{d,m}$ is the bias correction for each decile, d, and model, m, $\overline{T_{d,o}}$ is the mean observationally based temperature, o, for each decile, d, and $\overline{T_{d,m}}$ is the mean temperature for each decile and model in the historical period. The bias correction is applied to model projections as:

$$T_{\text{corr}_{\text{day,d,m}}} = T_{\text{uncorr}_{\text{day,d,m}}} + C_{d,m}$$

where $T_{\text{corr}_{d,m}}$ is a single corrected model temperature for a day falling into decile d in the model's distribution. See SI figure 7 for the results of this bias correction procedure.

2.11. Global mean temperature (GMT) change

Time periods with global mean temperature changes near 1 °C, 2 °C, 3 °C, and 4 °C are extracted from each model by selecting years by the following criteria:

$$W - 0.25\,^{\circ}\text{C} < \text{GMT}_y - \text{GMT}_{1981-2005}$$
$$+ \left(\text{GMT}_{\text{NCEP}-20\text{CR}-1981-2005}\right.$$
$$\left. - \text{GMT}_{\text{NCEP}-20\text{CR}-1850-1900}\right) < W + 0.25\,^{\circ}\text{C}$$

where W is the target level of global mean warming, GMT_y is the globally averaged temperature in each climate model in year y; $\text{GMT}_{\text{NCEP}-20\text{CR}-1981-2005}$ and $\text{GMT}_{\text{NCEP}-20\text{CR}-1850-1900}$ are the globally averaged temperatures as recorded in the NCEP 20th century reanalysis [32] in the pre-industrial (1850–1900) and the historical (1981–2005) periods, respectively; and $\text{GMT}_{1981-2005}$ is the globally averaged temperature in each CMIP5 model in the historical (1981–2005) period. The NCEP 20th century reanalysis is used to estimate the global mean temperature change that occurred between the pre-industrial period (1850–1900) and the end of the CMIP5 historical runs (1981–2005).

2.12. Global power system scenarios

Four scenarios of global power system growth are assessed. (a) Constant: the number, capacity, and location of power plants remain the same as in 2018; (b) 40 year lifespan: each power plant is assumed to have a 40 year lifespan and allowed to retire 40 years after its construction date. No new plants are constructed. (c) International Energy Agency (IEA) sustainability: projections taken directly from the IEA scenario through 2040. After 2040, the same rate of global decline in thermal power plant capacity as projected by the IEA between 2017 and 2040 is applied to each global power plant, proportionally to that plant's capacity, until total thermal capacity reaches zero near 2100. (d) IEA stated policies: projections taken directly from the IEA scenario through 2040. After 2040, the same rate of global increase in thermal power plant capacity as projected by the IEA between 2017 and 2040 is applied to each global power plant, proportionally to that plant's capacity, through 2100.

2.13. Curtailment model projections

Curtailment is calculated at an hourly scale using historical or modeled temperature and runoff. Monthly and annual aggregate outages are calculated by using the curtailment model to compute plant capacity for every power plant in the U.S. and E.U. region in 2018. These computations are performed for each hour in the historical period (1981–2005) and for each hour in all selected years at each GMT warming level for each CMIP5 model. Hourly temperature time series for each model are computed by linearly interpolating between each model-day's minimum and maximum temperatures, and then each hourly temperature is matched with the corresponding monthly runoff anomaly. The plant outage percentage is multiplied by the total plant capacity to give outage in GW. This outage in GW is then multiplied

by the time period to give an outage in TWh. The outages are summed and divided by the total capacity of all U.S.–E.U. plants to give the outage as a fraction of the total U.S.–E.U. capacity in 2018.

Curtailment is computed for the four power system scenarios defined above by calculating curtailment at each global power plant in each year between 2020 and 2090 on the hottest day per year at each plant. Curtailment is calculated using each CMIP5 climate model and each empirical curtailment estimate (10th, 50th, 90th percentile), and the mean curtailment across CMIP5 models is computed. Uncertainty in climate outcomes can be represented by the range of curtailment levels across CMIP5 models, all run under RCP 4.5 [33]. We show this range in figure 4(C) at the year 2040, which is the end point of the IEA projections, and also a time when higher and lower emissions scenarios have yet to significantly diverge from each other.

The cost of curtailed generation is calculated by multiplying a globally estimated levelized cost of electricity [34] of $0.1–$0.2 per kWh (in 2019 dollars) by the 2080s aggregated curtailment under each energy system scenario. The range in cost includes both the range across levelized cost of electricity estimates and the range in curtailment outcomes across CMIP5 models.
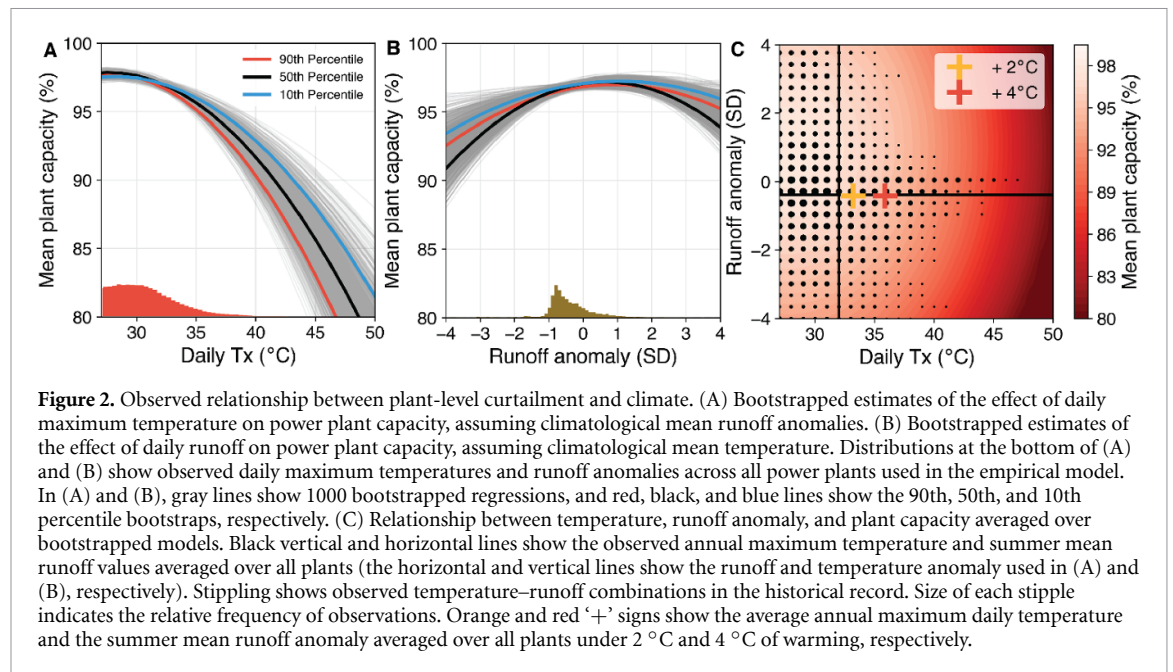
3. Results and discussion

Observed plant-specific air temperature and runoff (figures 1(A)–(C)), electricity demand (figure 1(D), derived from U.S. subgrids [25]), and plant outages (figure 1(E)) are tightly coupled at all thermal power plant sites with available daily-scale outage data [28, 35] (figure 1(A)). In the U.S., electricity demand peaks in boreal summer and winter due to energy use for heating and cooling buildings [12, 13]. Power plant outages in the U.S. and the E.U. (figure 1(E)) have a distinct seasonality that is inversely related to electricity demand and temperature: most outages are planned (e.g. for maintenance, or because their capacity is unnecessary) and occur in the fall and spring when electricity demand is lowest.

In the winter and particularly in the summer, when electricity is needed most, outages are generally less than 5% to ensure peak demand is met (figure 1(E)). Importantly, many grids overbuild their electricity supply to ensure that it can meet this peak demand [36]; however, this means there is considerably less tolerance for unplanned outages during the summer months, when temperatures are potentially too high or water levels too low for effective plant cooling. Because summertime electricity demand is high, daily outages that occur in the summer are mostly unplanned and may be related to weather or technical problems—and, as we find, can be predicted by daily air temperature and monthly-scale runoff.

Global mean temperature (GMT) projections of 2 °C and 4 °C above a 1850–1900 pre-industrial reference amplify these present-day patterns: plant-specific temperatures increase in all months (figure 1(B)), while plant-specific warm season runoff decreases (figure 1(C)). The modeled seasonal runoff peak shifts earlier in the spring in the future, possibly due to earlier snowmelt and a shift of precipitation type from snow to rain. Based on the historical association between air temperature and U.S. electricity demand, warming alone is sufficient to increase peak electricity demand in the U.S. by 10–20 and 30–50 percentage points under 2 °C and 4 °C of warming, respectively (figure 1(D)). This rise is in line with other recent estimates of the effect of warming on electricity demand, is largely driven by increased air conditioning use [11–13, 37–39], and will necessitate new generation capacity, even absent economic growth or population increases [37]. Furthermore, electricity demand increases are likely to be much larger in parts of the developing world, particularly in the tropics, where climate change, population growth, and rising incomes will converge to drive widespread expansion in electricity usage [11].

Beyond growing demand, warm temperatures present a systemic risk to thermal power plants, particularly during times of peak electricity demand (figure 2; raw data used in model fitting shown in SI figure 6). Across all plants for which daily outage data is available, electricity generation is maximized near the present-day plant-specific average summertime daily high air temperature (∼27 °C) and monthly runoff anomaly (∼0 SD), suggesting that plants are well-optimized for their historical mean climate conditions. However, plant capacity in the U.S. and E.U. declines nonlinearly at higher than average air temperatures (figure 2(A)) and at lower (and higher) than average runoff levels (figure 2(B)) during the summer months, explicitly accounting for plant cooling system type (recirculating or once-through), plant construction date, and individual plant characteristics, including the local climate, geography, regulations, and operating procedures (the effect of plant cooling system type and construction date are shown in SI figure 5). The cooccurrence of observed temperature and runoff emphasizes that plant capacity declines rapidly in temperature regardless of runoff (figure 2(C)). Furthermore, the average annual maximum daily temperature and mean summertime runoff responses to global warming across all sites ('+' signs in figure 2(C)), show that while plants are optimized to the present climate, they are not to a warmer future climate.

Our empirical estimate of curtailment's association with climate leverages the fact that summertime outages are generally unplanned (figure 1(E)) because electricity demand is highest on the hottest days when curtailment is most likely to occur.

Figure 2. Observed relationship between plant-level curtailment and climate. (A) Bootstrapped estimates of the effect of daily maximum temperature on power plant capacity, assuming climatological mean runoff anomalies. (B) Bootstrapped estimates of the effect of daily runoff on power plant capacity, assuming climatological mean temperature. Distributions at the bottom of (A) and (B) show observed daily maximum temperatures and runoff anomalies across all power plants used in the empirical model. In (A) and (B), gray lines show 1000 bootstrapped regressions, and red, black, and blue lines show the 90th, 50th, and 10th percentile bootstraps, respectively. (C) Relationship between temperature, runoff anomaly, and plant capacity averaged over bootstrapped models. Black vertical and horizontal lines show the observed annual maximum temperature and summer mean runoff values averaged over all plants (the horizontal and vertical lines show the runoff and temperature anomaly used in (A) and (B), respectively). Stippling shows observed temperature–runoff combinations in the historical record. Size of each stipple indicates the relative frequency of observations. Orange and red '+' signs show the average annual maximum daily temperature and the summer mean runoff anomaly averaged over all plants under 2 °C and 4 °C of warming, respectively.
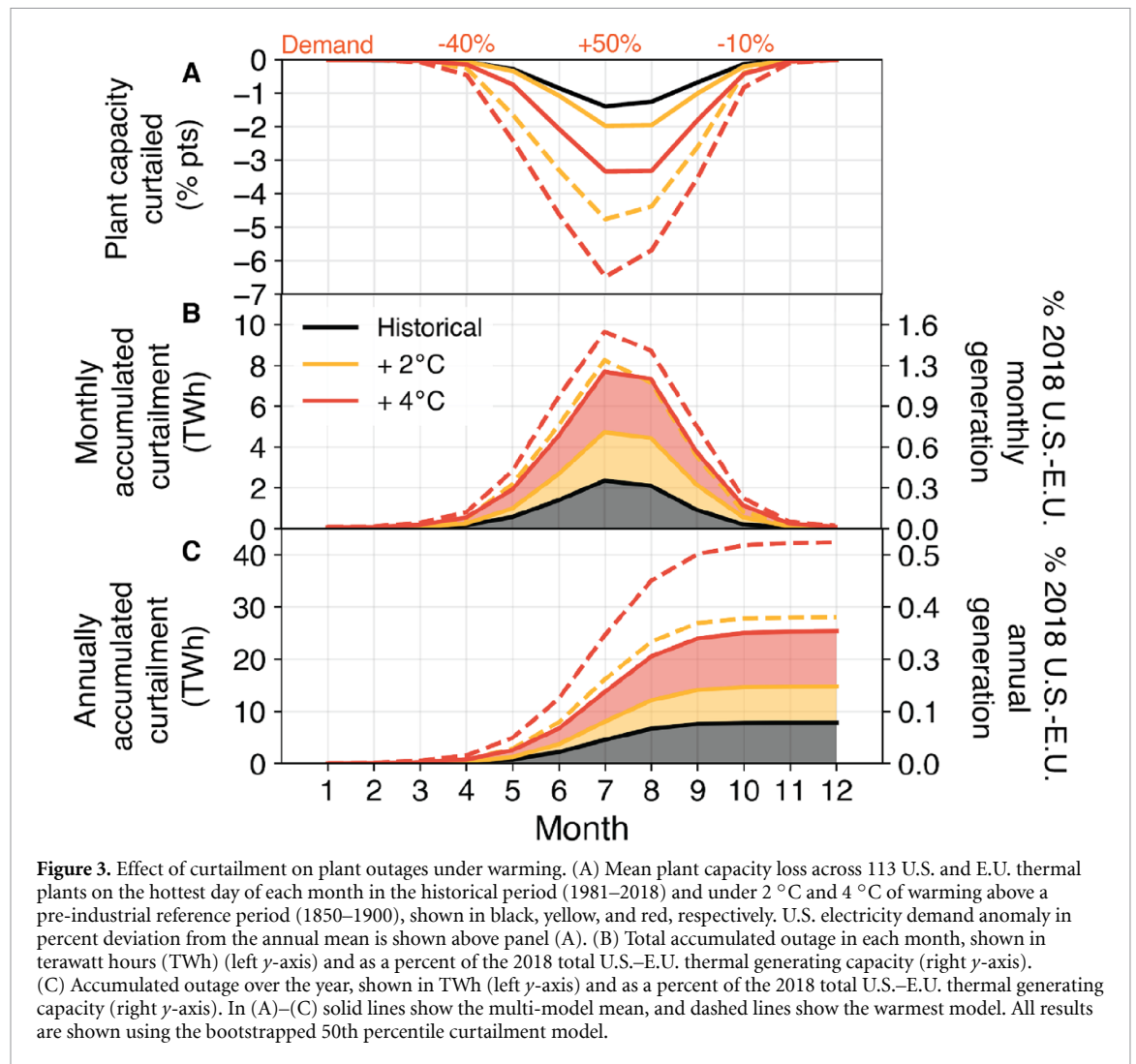
Furthermore, our model directly considers the variation in plant cooling system (once-through or recirculating) and plant age, and it indirectly considers geographic location and regulatory and enforcement regimes through plant-specific fixed effects. Additionally, cooling requirements depend on a power plant's thermal efficiency, which varies more with plant age than with plant fuel type [40], meaning that the large number of nuclear plants in our dataset is unlikely to significantly bias our estimates of the temperature–curtailment relationship. Together, these factors make our estimate of curtailment extendable into the future and to thermal power stations across the world (figures 3 and 4). However, because newer gas combined cycle power plants require less cooling than other thermal plants and are becoming more common [41], heat-related curtailment at these plants may be less than estimated by our model. At the same time, solar photovoltaic and concentrated solar power (CSP) plants are also subject to heat-related efficiency loss, and these losses are not accounted for in our analysis, potentially increasing the overall risk of reduced electricity generation due to warming.

Future climate warming increases U.S.–E.U. thermal power plant curtailment, creating an electricity supply gap that will need to be filled by additional (and unaccounted for [15]) electricity production. With warming, plant capacity on the hottest summer day across all U.S.–E.U. thermal power plants falls by a mean projection of 2.0 percentage points under 2 °C of global warming and 3.1 percentage points under 4 °C of warming (figure 3(A)). These results are in line with region-specific studies that use power plant modeling approaches to estimate climate change impacts on thermal plants [5, 15, 16, 20]. While the acute effects of curtailment

on grid stability will be felt at the hourly scale, economic losses to power plants will be aggregated over the year; accordingly, we show the accumulation of estimated heat-related curtailment across the year. In summer, our empirical model projects monthly aggregated curtailment increasing by 100%–300% under 2 °C and 4 °C of warming, respectively, resulting in a total loss of 0.6%–1.5% (across warming scenarios and bootstrapped curtailment models) of total U.S.–E.U. thermal generating capacity in July–August (figures 3(B) and (C)). This percentage loss is not dependent on installed capacity: the total capacity (in GW) that is curtailed will increase in the future as global installed capacity grows.

We apply our empirical curtailment model to all global thermal power plants using plant data from the World Resources Institute [29], bias-corrected climate projections from the CMIP5 ensemble, and four scenarios of future energy system development including two from the IEA, ranging from a rapid phase-out of thermal power plants to their continued growth (figures 4(A)–(C)). The mix of electricity generation technologies deployed globally strongly determines the extent and costs of future curtailment (figure 4(D)). Because data on global power plant cooling systems is not available, we test the sensitivity of our projections to cooling system type by running our model once assuming all plants have once-through cooling and again assuming all plants have recirculating cooling (figure 4(D)), finding that recirculating systems result in about 25 TWh more annually averaged curtailment in the 2080s. While power plant economics are complex and depend on electricity prices, construction, and operating costs, we present a simple estimate of potential global losses due to heat-related curtailment. Using a levelized cost of electricity ranging from $0.10 to $0.20 per kWh

Figure 3. Effect of curtailment on plant outages under warming. (A) Mean plant capacity loss across 113 U.S. and E.U. thermal plants on the hottest day of each month in the historical period (1981–2018) and under 2 °C and 4 °C of warming above a pre-industrial reference period (1850–1900), shown in black, yellow, and red, respectively. U.S. electricity demand anomaly in percent deviation from the annual mean is shown above panel (A). (B) Total accumulated outage in each month, shown in terawatt hours (TWh) (left *y*-axis) and as a percent of the 2018 total U.S.–E.U. thermal generating capacity (right *y*-axis). (C) Accumulated outage over the year, shown in TWh (left *y*-axis) and as a percent of the 2018 total U.S.–E.U. thermal generating capacity (right *y*-axis). In (A)–(C) solid lines show the multi-model mean, and dashed lines show the warmest model. All results are shown using the bootstrapped 50th percentile curtailment model.
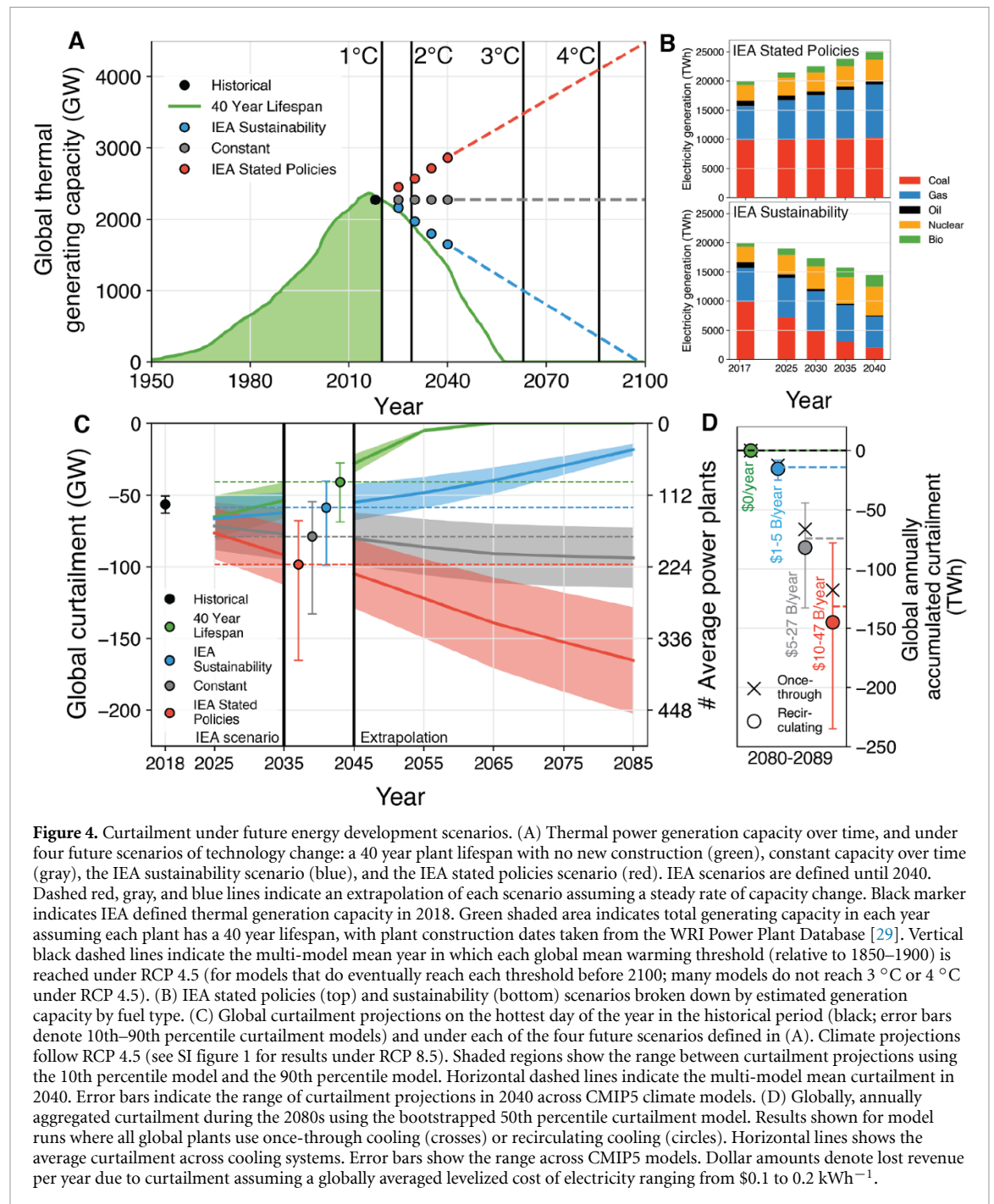
[34], projected aggregated curtailment translates into lost revenue of up to $47 billion per year by the end of the century under the IEA stated policies scenario, where thermal plant capacity continues to increase, versus $1 billion per year should the world follow the IEA sustainability scenario and mostly phase out thermal power production by 2100.

While regulatory and technology changes could modify the fundamental relationship between temperature and thermal power generation capacity, many existing power plants will operate for decades as the climate warms [6], making it important to understand the drivers of uncertainty in climate-related curtailment. Three factors dominate this uncertainty: observed empirical model uncertainty (across bootstrapped estimates, accounting for technology, geography, operating procedures, and regulation), warming uncertainty (across climate models in the same emissions scenario), and the trajectory of the power system's fuel mix (across energy system scenarios). By the end of the century, the energy system scenario is the largest contributor to uncertainty in curtailment projections as it determines the number of thermal power plants at which curtailment

might be necessary. Furthermore, several factors will affect future curtailment that are not accounted for here. First, power system trajectories and warming are linked. Under a scenario where thermal power plants are rapidly decommissioned, there will likely be less warming than if thermal generating capacity continues to grow, dampening curtailment. Second, our model considers the average response across plants; as such individual plants could be more or less impacted by heat extremes than the ones providing daily outage data. Third, there is substantial uncertainty in the runoff projections generated by CMIP5 models. Plant-specific runoff could evolve differently than the models suggest due to land use change, climate change, and the relatively simple runoff modeling schemes in current Earth system models [42, 43]. Additionally, in a warmer and drier climate, thermal power plants may be modified to more efficiently recirculate cooling water or find alternative water sources in times of drought [17], reducing heat-related curtailment.

Importantly, there is uncertainty about how power plants operating in different climates, and with different fuel types, cooling systems, capacities, and

Figure 4. Curtailment under future energy development scenarios. (A) Thermal power generation capacity over time, and under four future scenarios of technology change: a 40 year plant lifespan with no new construction (green), constant capacity over time (gray), the IEA sustainability scenario (blue), and the IEA stated policies scenario (red). IEA scenarios are defined until 2040. Dashed red, gray, and blue lines indicate an extrapolation of each scenario assuming a steady rate of capacity change. Black marker indicates IEA defined thermal generation capacity in 2018. Green shaded area indicates total generating capacity in each year assuming each plant has a 40 year lifespan, with plant construction dates taken from the WRI Power Plant Database [29]. Vertical black dashed lines indicate the multi-model mean year in which each global mean warming threshold (relative to 1850–1900) is reached under RCP 4.5 (for models that do eventually reach each threshold before 2100; many models do not reach 3 °C or 4 °C under RCP 4.5). (B) IEA stated policies (top) and sustainability (bottom) scenarios broken down by estimated generation capacity by fuel type. (C) Global curtailment projections on the hottest day of the year in the historical period (black; error bars denote 10th–90th percentile curtailment models) and under each of the four future scenarios defined in (A). Climate projections follow RCP 4.5 (see SI figure 1 for results under RCP 8.5). Shaded regions show the range between curtailment projections using the 10th percentile model and the 90th percentile model. Horizontal dashed lines indicate the multi-model mean curtailment in 2040. Error bars indicate the range of curtailment projections in 2040 across CMIP5 climate models. (D) Globally, annually aggregated curtailment during the 2080s using the bootstrapped 50th percentile curtailment model. Results shown for model runs where all global plants use once-through cooling (crosses) or recirculating cooling (circles). Horizontal lines shows the average curtailment across cooling systems. Error bars show the range across CMIP5 models. Dollar amounts denote lost revenue per year due to curtailment assuming a globally averaged levelized cost of electricity ranging from $0.1 to 0.2 kWh^{-1}.

regulatory regimes, will vary in their response to high temperatures. Because daily-scale power plant outage data is very limited, we estimate this relationship using all available data, which primarily comes from U.S. nuclear plants and some coal, oil, and gas plants from the E.U. This dataset samples a wide range of power plant capacities across different climates. However, this limited data may over- or under-estimate the global consequences of heat-related curtailment. Notably, there is no available data from developing countries where most future power plant construction will take place. Accordingly, our analysis—and our understanding of climate change impacts on the energy sector—could be expanded

and our projections improved by additional daily- or sub-daily-scale power plant outage data availability from a diverse set of power plants across the world.

Our results suggest that thermal power plant curtailment could have substantial impacts on global electricity generation capacity during the hottest parts of the year, necessitating additional overbuilding of the global electricity system by up to 1%–7% given the current generating technology mix. At the same time, the magnitude of this impact depends on our adaptation decisions: if we rapidly transition the electricity sector to non-thermal power sources like solar and wind, curtailment can be greatly reduced, although hydropower may face substantial future risk

from reduced streamflow [17]. Our results highlight the double benefit from non-thermal electricity generation in a warmer world: less curtailment and fewer emissions.

Data availability statement

The data that support the findings of this study are openly available at the following URL: www.ethancoffel.com/data/electricity/.

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Author contributions

E D C and J S M conceived the study, designed the methodology, and collated the data. E D C performed the analysis. E D C and J S M interpreted the results and wrote the manuscript.

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