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A data-driven approach to investigate the impact of air temperature on the efficiencies of coal and natural gas generators

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HIGHLIGHTS

- Dry-cooled generators are most negatively impacted by rises in air temperature.
- Cooling water conditions are better predictors for wet-cooled generator efficiency.
- Natural gas combustion units in hot and dry areas likely utilize inlet air cooling.

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ABSTRACT

The efficiency of a thermoelectric generator is dependent on a number of operational and climatic variables, including ambient air temperature. To date, there has not been a data-driven analysis of the impacts of climate variability on electricity generator performance that includes a statistically representative set of generators. This study develops regression models to estimate changes in the efficiencies of over one thousand coal and natural gas generators as a function of ambient air temperature and operational variables, across different fuel types, prime movers, cooling systems, and climate zones during the years ranging from 2008 to 2017. The efficiencies of generators with dry cooling, particularly those in hot and dry climates, demonstrated the greatest sensitivity to increases in ambient temperature. Results for generators utilizing wet cooling systems were largely inconclusive, most likely because other factors, such as cooling water temperature, are better predictors of efficiency. Natural gas combustion generator efficiencies exhibit large sensitivities to rises in air temperature in theoretical models but had a counterintuitive trend in our findings, where losses were relatively small in the hottest and driest climates. This result is likely due to the fact that natural gas combustion generators in hot and arid regions often utilize inlet air cooling technologies to reduce the temperature of ambient air before it enters the compressor, thereby mitigating efficiency losses. The analytical framework developed offers generalized methods for cleaning, processing, and merging federally available electricity generation and climate datasets to increase their value in future studies.

1. Introduction

Thermal power production, accounting for 83% of total electricity generation, contributed to 28% of greenhouse gas (GHG) emissions [1], 50% of sulfur dioxide (SO_2) emissions, 10% of nitrogen oxide (NO_x) emissions [2], 40% of freshwater withdrawals [3], and 3% of freshwater consumption [3] nation-wide in 2017. Coal and natural gas-fueled generators alone contributed 74% of thermoelectric generation (62% of total electricity generation) [1], and thus, a significant fraction of these environmental impacts associated with the U.S. power sector. The GHG emissions, air pollutants, and cooling water usage associated with power production depend on the efficiency of the electricity generating unit (EGU), which is influenced by factors such as fuel type, prime mover, cooling system, and pollution controls. Less efficient EGUs generally require more fuel and cooling water to generate one unit of electricity.

The impacts of climate variability and/or climate change on the operational capacity and efficiency of electricity infrastructure has been studied in past analyses. Several studies in the literature have analyzed the influence of climate change on power infrastructure using thermodynamic modeling. Studies utilizing thermodynamic models to assess the impact of temperature increases on gas turbine efficiency found that a 1 °C increase in temperature correlates to an efficiency decrease of approximately 0.1% [4,5]. Maulbetsch and DiFilippo studied natural

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gas combined-cycle power plants in four different environments and found that recirculating tower cooled power plants and dry-cooled power plants experienced capacity reductions between 0.3–0.5% and 0.7% per 1 °C increase in air temperature, respectively [6]. Erdem and Sevilgen showed that the electricity generation of a gas turbine can decrease by 1.67–6.22% when temperatures surpass 15 °C [7].

Other analyses have utilized an integrated modeling approach to assess changes in the electricity grid due to climate change. Van Vliet et al. applied a hydrology-electricity modeling framework to predict that during the period spanning 2031–2060, approximately 4.4–16% and 6.3–19% of thermoelectric generation in the U.S. and Europe, respectively, will be lost [8]. They also found that by the 2050s, thermal power plants globally could experience capacity reductions of 7–12% [9]. Sathaye et al. used temperature projections from general circulation models to estimate changes in natural gas power plant capacity in California and found that 1.1–4.6% of peak capacity could be lost by the end of the century [10]. Bartos and Chester combined climate, hydrology, and thermodynamic power plant models to estimate a 1–3% reduction in summer generating capacity by mid-century in the Western U.S., with reductions up to 7–9% when analyzed within the context of a ten-year drought scenario [10]. Cook et al. used a combination of regression, climate, and thermodynamic modeling to find that a 1 °C rise in cooling water temperature can lead to a 0.15–0.5% decrease in power output [11]. Liu et al. assessed the impact of climate change and thermal discharge regulations on thermoelectric generators in the U.S. using a regional Earth system model and a thermoelectric power generation model. The study found that by the 2060s, climate change alone could reduce generation capacity by 2–3%, but environmental regulations could actually raise capacity reductions up to 12% if power plant operators are forced to curtail operation when water discharge temperatures exceed legal limits [12]. Miara et al. used the coupled Water Balance Model and Thermoelectric Power and Thermal Pollution Model (WBM-TP2M) to project changes in U.S. thermoelectric power plant capacity due to water constraints and climate change and found that under modeled contemporary climate scenarios, once-through-cooled power plants experience the greatest reduction in capacity [13].

Only a handful of studies have statistically modeled the relationship between generator efficiency and climatological parameters based on real-world empirical data [14,15], and only one has been a peer-reviewed journal publication [16]. Henry and Pratson used regression modeling to develop a relationship between climate parameters (water and air temperature) and generator efficiency [16]. The study indicated that once-through cooled generators will experience a change of −0.11% to −0.05% in efficiency per 1 °C increase in intake water temperature and an efficiency change of −0.02% to +0.05% per 1 °C increase in intake ambient air temperature based on a sample of 20 once-through power plants. The study also found that power plants with recirculating cooling systems had an efficiency change ranging from −0.06% to +0.04% per 1 °C increase in wet-bulb temperature based on a sample size of 19 power plants. Because Henry and Pratson's study only analyzed water-cooled thermal power plants, natural gas fired combustion generators and dry-cooled generators were not included in their analysis. Furthermore, their limited samples of 20 once-through-cooled and 19 recirculating-cooled power plants might not be sufficient for capturing variability across different fuels, prime movers, cooling systems, and local climate.

With predicted climate change expected to increase air temperatures, it is important to understand how generators react to changes in climatic parameters as changes in the performance of generators will consequently affect pollutant emissions, GHG emissions, and water usage. As much of the prior body of work described above utilizes theoretical physics-based models to establish predicted capacity reductions, to date there is a lack of data-driven studies that quantify the historical relationship between power plant efficiency and changes in temperature for a statistically significant population of power plants. Here we investigate how the efficiencies of real-world thermoelectric generators respond to changes in ambient air temperature, as the operational and climatic variables affecting the performance of operational power plants are typically too complex to capture in purely theoretical models. We also look at how the responses vary across fuel types, prime mover, and cooling type. To do so, we utilize regression modeling, applied to over one thousand EGUs (representing 618 unique power plants) to assess and critique the capability of federally available datasets to support such an analysis. To the best of the authors' knowledge, this will be the first study to look at the impact of air temperature on generator efficiency based on a statistically representative set of electricity generating units. We also comment on how federal datasets could be improved for usability to facilitate more data-driven studies in the future.

2. Methods

2.1. Preparing operational datasets for the regression analysis

A series of datasets characterizing each EGU in terms of its technical configuration and historical operational data were cleaned, filtered, and processed to prepare the data required for the regression analysis. In this study, the term "EGU" is used to represent a coal steam (CL-ST) generator, natural gas combustion (NG-GT) generator, natural gas steam (NG-ST) generator, or natural gas combined-cycle (NG-CC) system. Data from the years 2008 to 2017 were considered.

Each EGU's fuel type, prime mover, cooling technology, and combined heat and power (CHP) status were characterized according to the U.S. Energy Information Administration's (EIA) Form 860, which provides information on every EGU over 1 MW nationally [17]. The EIA 860 Form assigns a unit code to each generator for identification. For coal steam, natural gas combustion, and natural gas steam EGUs, no unit code is usually given, as each generator is its own unit. For natural gas combined-cycle systems, multiple generators share a single unit code. Thus, each coal steam, natural gas combustion, and natural gas steam EGU refers to a single generator, whereas a natural gas combined-cycle EGU refers to all generators that share the same unit code. Nameplate capacity for each generator was aggregated to the EGU level. Generators are linked to its respective boiler(s), and each boiler is linked to its respective cooling system (if any is used).

This analysis focused on EGUs that utilize natural gas and coal as fuel and excluded all combined heat and power units. For coal steam, natural gas steam, and natural gas combined-cycle EGUs, only those with once-through without cooling pond (ON), once-through with cooling pond (OC), recirculating with cooling pond (RC), recirculating with towers (RT) and dry (DRY) cooling were considered. (Cooling systems classified as "other" or "hybrid" in the EIA dataset were excluded from the study.) Natural gas combustion EGUs, which do not utilize wet or dry cooling systems, were labeled as having a cooling system of "NONE (GT)". Units with one or more cooling systems of the same type across an entire year were kept in the final dataset, but instances where a unit had (1) more than one cooling type within the year of analysis and/or (2) changed, added, or removed a cooling system within the course of a single year of analysis were removed. For example, if an EGU and its respective cooling system began operation in May 2009, only data from 2010 and onward for that EGU was used. Similarly, if a generator that began operation before 2008 switched from a once-through cooling system to a recirculating cooling system in August 2012, the entire year of 2012 is removed from that EGU's data.

Hourly gross load (MWh) and heat input (MMBtu) data were obtained from Environmental Protection Agency's (EPA) Air Markets Program Data (AMPD) [18]. The AMPD provides continuous emissions monitoring (CEM) data for generators that are required to monitor under the EPA's Clean Air Markets Programs [18]. The AMPD classifies collection methods for heat input data into one of the following categories: "Measured", "Calculated", "Substitute", "Measured and Substitute", "Not Applicable", "Undetermined", "Unknown Code". For this analysis, we used only observations where the heat input was labeled as "Measured".

While the power plant codes between the two datasets were fairly consistent in the years analyzed, the generator/boiler IDs had much greater variance. A script was developed to detect naming patterns and inconsistencies to match as many generators as possible. While most generators were matched with this method, a few had to be matched manually. Difficulties in joining the EIA and EPA datasets are elaborated further in the discussion.

After matching units between the EIA and EPA datasets, the heat rate (HR), efficiency (η), and capacity factor (CF) at every hour were calculated using Eqs. (1)–(3), respectively. The heat input is the primary energy used to generate the electricity load. The heat rate (with units of MMBtu/MWh) is the amount of energy used to generate one unit of electricity and is calculated by dividing the heat input by the gross load. The efficiency is the percentage of primary energy that gets converted into electrical energy and is calculated by multiplying the inverse of the heat rate by a conversion factor. Capacity factor refers to the percentage of the total nameplate capacity at which the EGU is operating over a period of time. In this analysis, we define the change in capacity factor, also referred to here as the ramping rate, as the difference in capacity factor from one hour to the next. The AMPD contained observations where measured heat rate were unreasonable or nonsensible. Lower and upper limits on hourly heat rate (for all nonzero gross load hours) were applied based on the limits developed by the EPA for their Power Sector Modeling Platform [19]. The limits are dependent on the fuel and prime mover configuration of the generating unit and are provided in Table A1.

$$HR = \frac{Hourly\ Heat\ Input\ [MMBtu]}{Hourly\ Gross\ Load\ [MWh]} \tag{1}$$

$$\eta = \frac{Hourly\ Gross\ Load\ [MWh]}{Hourly\ Heat\ Input\ [MMBtu]} \times \frac{3.412\ [MMBtu]}{[MWh]} \tag{2}$$

$$CF = \frac{Hourly\ Gross\ Load\ [MWh]}{Nameplate\ Capacity\ [MW] \times 1\ h} \tag{3}$$

Upon inspection of the heat rates, it became apparent that some natural gas combined-cycle EGUs in the EPA dataset reported operational data for only the gas turbine part of the natural gas combined-cycle EGUs, while others reported data representative of the entire unit [18]. All natural gas combined-cycle EGUs with duct burners, a technology added to heat recovery steam generators to increase their high-pressure steam output, should report generation (i.e., gross load) from the entire unit (i.e., both the steam cycle and gas cycle generation), whereas units without duct burners are not mandated to report steam generation. (The heat input of all components of a natural gas combined-cycle EGU is reported regardless due to emissions monitoring regulations.) More information on the reporting procedures can be found in the EPA Emissions Monitoring Policy Manual [20] and the Clean Air Markets Emissions Collection and Monitoring Plan System Reporting Instructions [21]. Fig. 1a illustrates a density plot of all reported heat rates from 2008 to 2017 of natural gas combined-cycle EGUs, separated according to whether the natural gas combined-cycle EGU has a duct burner as reported by the EIA Form 860 [17]. All duct burner classifications are determined by year; thus, a natural gas combined-cycle EGU could be classified as having a duct burner in some years but not others. The majority of calculated heat rates for the EGUs with reported duct burners range from 5.5 to 10 MMBtu/MWh (Fig. 1a, left), which is consistent with the average heat rate of natural gas combined-cycle EGUs [22]. However, the density plot shown in for the units without duct burners (Fig. 1a, right) is bimodal, with about half of the heat rates ranging from 5.5 to 10 MMBtu/MWh and the other half ranging from 10 to 15 MMBtu/MWh (i.e., consistent with just the gas turbine part of the natural gas combined-cycle EGU). This bimodal distribution indicates that for natural gas combined-cycle generating

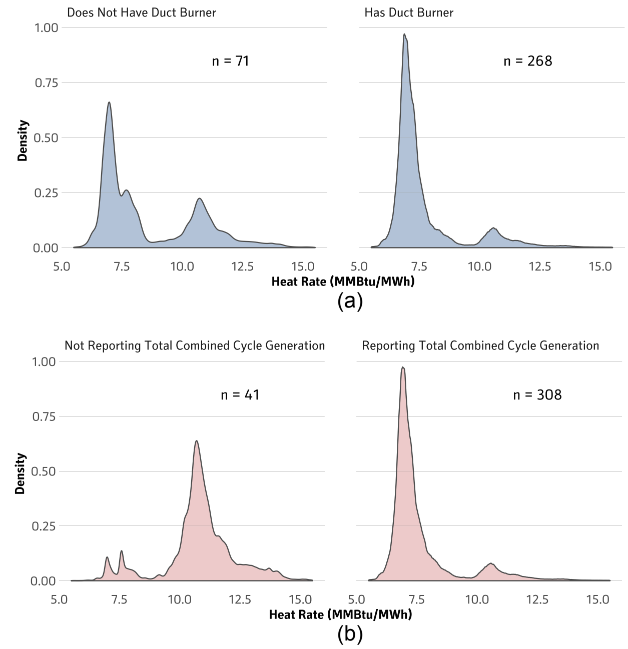

Fig. 1. (a) Hourly heat rates for natural gas combined-cycle electricity generating units are plotted and categorized by whether each unit has a duct burner or not for each operating year, based on EIA Form 860 data [17]. The density plot for units with duct burners show a unimodal distribution between 5.5 and 10 MMBtu/MWh. The plot for units without duct burners show a bimodal distribution, with one distribution ranging from 5 to 10 MMBtu/MWh and another ranging from 10 to 15 MMBtu/MWh. (b) Hourly heat rates for natural gas combined-cycle electricity generating units are plotted and categorized by whether each unit is reporting steam generation based on our proposed classification methodology. Units with duct burners were automatically classified as reporting steam generation, while units without duct burners were classified based on the 90th percentile of their hourly heat rates each year.

units that do not have duct burners, some operators report generation from both the steam and gas cycles, whereas other operators only report the gas generation.

Consequently, natural gas combined-cycle EGUs had to be recategorized to determine whether the entire system's generation or just the gas cycle generation was reported in the EPA dataset to prevent misinterpretation of the calculated heat rates. Natural gas combined-cycle EGUs reported as having a duct burner in the EIA 860 form were automatically marked as reporting both steam and gas generation. More analysis was required for EGUs that did not report a duct burner. For each natural gas combined-cycle EGU, the 90th quantile of the hourly heat rates within each calendar year of study was calculated. A density plot of the 90th percentiles showed a similar bimodal distribution to the units without duct burners in Fig. 1a, with a split between 5.5 to 10 MMBtu/MWh and 10 to 15 MMBtu/MWh. Accordingly, all natural gas combined-cycle EGUs that had a 90th percentile heat rate value equal to or less than 10 MMBtu/MWh were categorized as "Reporting Total Combined Cycle Generation". A natural gas combined-cycle generating unit with a 90th percentile heat rate above 10 MMBtu/MWh was marked as "Not Reporting Total Combined Cycle Generation", meaning that only the gas generation of the combined-cycle EGU was reported.

The revised classification of units is illustrated in the density plot of heat rates shown in Fig. 1b. In comparing Fig. 1a and b, the bimodal distribution in Fig. 1b is much less prominent for units not reporting steam generation, with the vast majority of heat rates falling in between 10 and 15 MMBtu/MWh. As for the units reporting steam generation, there is a unimodal distribution, with most heat rates ranging from 5.5 to 10 MMBtu/MWh.

There are still some observations that do not fall within the larger distribution, which is most likely due to increased heat rate (decreased efficiency) during hours where the generating unit is rapidly increasing or decreasing its output, commonly referred to as a period of ramping. (The ramping rate refers to an increase or decrease in an EGU's electrical output per unit time.) Since ramping would likely obscure any impact of temperature on unit efficiency, we attempted to eliminate any operational data occurring during hours of significant ramping. The change in capacity factor from one hour to the next (i.e., ΔCF) was used as a proxy to detect ramping up or down during generation, in efforts to remove these periods from skewing the efficiency analysis. The ΔCF at each hour t (ΔCF_t) was calculated by subtracting the capacity factor at said hour t (CF_t) from the capacity factor at the previous hour (CF_{t-1}). For hours where operational data were missing (either due to the EPA dataset not having the data or due to the data being filtered out), the ΔCF could not be calculated for the following hour, and a value of "NA" (not available) was assigned to ΔCF. All hours with a ΔCF of "NA" were removed from the analysis. After calculating the ramp rate at every hour for all units, hours with a gross load of "0" MW were also removed.

When plotting the efficiency versus capacity factor for natural gas combined-cycle EGUs, two clusters were often found (e.g., one smaller cluster of lower hourly capacity factor values and a larger cluster of higher hourly capacity factor values). Having two clusters would skew the regression, so the smaller cluster containing fewer hourly capacity factor values (since these values were less representative of the typical operation of the EGU) were removed. Density-based clustering, through the `dbscan` package in R [23], was implemented to detect two clusters of efficiency versus capacity factor for every natural gas combined-cycle unit. The cluster with the lowest count of observations was removed from the dataset. (On average, approximately 74% of each NG-CC unit's data were part of the larger cluster.) By analyzing the most prominent cluster of operational capacity factor values, each regression considered hours at which the EGUs generated electricity within similar operational conditions, thus reducing the impact of other operational characteristics on efficiency variability (e.g., operating at a high versus low capacity factor).

To remove other outliers in the operational data, observations where the efficiencies and capacity factors were not within the 5th and 95th percentiles (of each respective generating unit) were omitted from the analysis. The distribution of ΔCF indicated that most values fell between -0.1 and 0.1 (i.e. signifying a change of operational output within 10% of the previous hour). Data in hours where the values of ΔCF fell outside of these bounds were omitted from the regression models, so that ramping did not skew the efficiency analysis. (On average, 96%, 87%, and 80% of the data records considered for CL-ST and NG-CC, NG-ST, and NG-GT generation units, respectively, fell within range and were kept for the analysis.).

2.2. Preparing climate datasets for the regression analysis

Local Climatological Data (LCD) from the National Oceanic and Atmospheric Administration (NOAA) were used to obtain ambient temperature [24]. The NOAA dataset includes hourly (and sub-hourly) dry-bulb temperature (T_{db}), wet-bulb temperature (T_{wb}), and relative humidity data from thousands of weather stations around the country. For instances where multiple observations were given within the same hour at a weather station, the average of each indicator (temperature, relative humidity, etc.) for that hour at was calculated.

The longitude and latitude of each power plant were retrieved from the EIA 860 form [17] and each power plant was matched to the nearest NOAA weather station for each year of EGU operation. The reason for assigning a weather station for each year is to account for instances where a weather station was installed closer to a power plant within the 2008–2017 timespan. Most power plants were within 20 km (12 mi) of a NOAA station. However, there were some plants where the nearest NOAA station was more than 30 km (18.6 mi) away, with a handful reaching up to 50 km (31 mi). (A map of the distance from each EGU to the nearest weather station is provided in Fig. A1.) For this analysis, we did not place a filter on records based on the maximum distance between power plant and weather station, but we acknowledge that the accuracy of climate data can decrease with increasing distance between the unit and weather station.

After assigning a weather station to each generating unit, climate data from NOAA were merged with operational data from the AMPD set. Any missing hourly data in the climate or operational datasets were removed from the analysis. To remove outliers in the climate data, the 1st and 99th percentiles for the wet-bulb and dry-bulb temperatures, respectively, were identified for each EGU. For EGUs with recirculating tower cooling systems, observations where the wet-bulb temperature did not fall within the 1st and 99th percentile wet-bulb temperatures were removed. For EGUs with all other cooling systems, the same methodology was applied for dry-bulb temperature. The reasoning behind why wet-bulb and dry-bulb temperatures were applied based on cooling system is explained in Section 2.3.

The impact of the local climate on the response of each EGU to temperature change was also analyzed. County-level climate zones, defined by the U.S. Department of Energy's (DOE) Building America Program, were utilized for data sorting purposes [25]. Based on climate regions developed by the Pacific Northwest National Laboratory for the International Energy Conservation Code, each county in the U.S. was classified to reflect one of seven climate zones: Marine, Very Cold, Cold, Mixed-Humid, Hot-Humid, Mixed-Dry, and Hot-Dry. Each EGU was assigned a climate zone based on the county it is located in.

2.3. Regression analysis

We developed a regression model to relate EGU efficiency with operational variables and ambient air temperature. An exponential relationship was observed between hourly capacity factor and efficiency data. For the relationship between efficiency and ΔCF, a symmetrical relationship was found: for negative values of ΔCF, as the magnitude increased, the efficiency of the EGU decreased. Conversely, as positive ΔCF values grew in magnitude, efficiency values decreased, suggesting that ramping an EGU up has a similar impact on efficiency as ramping operations down. Thus, ΔCF was fitted as linear spline, with a knot at $\Delta CF = 0$. We acknowledge that some generating unit types, such as natural gas combustion units, are more susceptible to ramping events than other unit types, such as coal steam units. However, by filtering out hours where ΔCF were below -0.1 and above 0.1, we aimed to remove instances where ramping would be the prominent influencing variable on efficiency. Furthermore, a priori analysis showed that having ΔCF versus not having ΔCF, as well as keeping unfiltered versus filtered ΔCF values, did not have significant impacts on the regression results.

For regressing efficiency versus temperature, choosing between dry-bulb and wet-bulb temperature is important. For natural gas combustion EGUs, the effect of humidity on the efficiency is minimal [26], and therefore the dry-bulb temperature was chosen as the dependent variable. Humidity typically does not have a significant effect on the efficiency of wet-cooled generating units, with the exception of units cooled with recirculating towers. In a recirculating cooling tower, steam is cooled to a temperature approaching wet-bulb temperature [26–29]. Thus, for EGUs with recirculating cooling towers, the efficiency was predicted using wet-bulb temperature. For dry-cooled generating units, the evaporation process is not used, and heat is transferred only to ambient air [29]. The steam is cooled to a temperature that reaches the dry-bulb temperature, and therefore the efficiencies of EGUs with dry cooling were predicted using dry-bulb temperature [30]. Once-through cooling systems and recirculating with cooling pond systems do not rely on the evaporative process (since water itself is used to remove heat), and as such, the efficiencies of EGUs utilizing once-through cooling and recirculating cooling with ponds were regressed against dry-bulb temperature.

Each hourly temperature value was binned to account for more drastic decreases in efficiency at higher ambient temperatures. The 50th, 75th, and 90th percentiles of temperature values (wet-bulb for recirculating tower-cooled and dry-bulb for all other cooling types) were calculated for each generating unit. Then, each hourly observation was assigned a temperature bin depending on if temperature value fell into one of the following categories: below the 50th percentile, between the 50th and 75th percentiles, between the 75th and 90th percentiles, and above the 90th percentile.

Before performing the regression, any EGU with less than 1000 hourly observations was removed from the analysis, as having a small number of observations can result to a skewed regression fit. Furthermore, we noticed that even if an EGU had more than 1,000 observations, it is possible that the number of observations per temperature category could be small (i.e., an EGU might only experience temperatures above the 90th percentile for 80 observations). Thus, any EGU that has less than 250 observations in any temperature category was excluded from the analysis as well. In the end, over one thousand

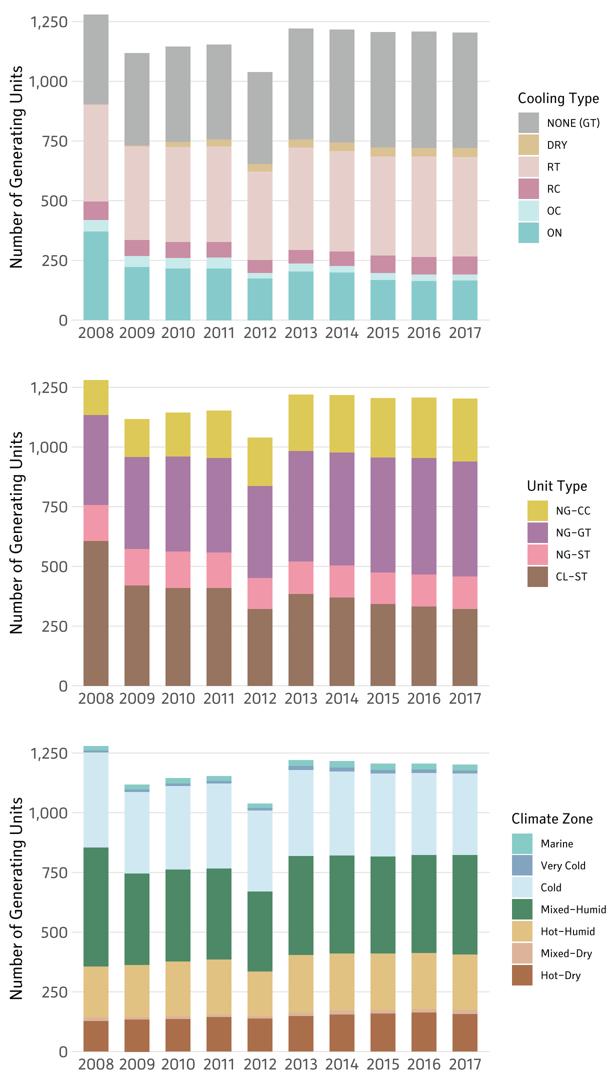

Fig. 2. The final number of electricity generating units included in the analysis, characterized by (top) cooling type, (middle) fuel type and prime mover technology, and (bottom) climate zone. The decrease in number of units in 2012 is due to a large number of NOAA weather stations missing temperature data in that year.

generating units (over the span of 2008 to 2017), representing 618 unique power plants, were analyzed (Fig. 2) Fig. A2 provides maps of each EGU analyzed in the study by year.

Because of the combination of linear and non-linear relationships between efficiency and the various variables we examined, non-linear least squares (NLS) analysis was utilized. The regression models shown in Eqs. (4) and (5) were used, where a (%/°C) is the coefficient relating the change in efficiency due to a unit degree Celsius increase in dry-bulb temperature (T_{db}), and b (%/°C) is the coefficient corresponding to change in efficiency due to a unit degree Celsius increase in wet-bulb temperature (T_{wb}). For both equations, the capacity factor is exponentially regressed to a power of k, with a coefficient of d (%) and the change in capacity factor is linearly fit with a coefficient of g. The ϵ is a mean-zero random error term. The models used here are similar to the ones developed by Henry and Pratson [16], who analyzed the impacts of water temperature and dry-bulb temperature on once-through cooling systems and the impact of wet-bulb temperature on recirculating cooling systems.

$$\eta_{DRY,RC,OT,NONE} = aT_{db} + dCF^k + g\Delta CF + \epsilon \tag{4}$$

$$\eta_{RT} = bT_{wb} + dCF^k + g\Delta CF + \epsilon \tag{5}$$

To ensure that there was not significant collinearity amongst regression variables, we performed diagnostic tests for the regression variables on a few dozen random generating units. We did not see a strong correlation between CF and ΔCF. Furthermore, there did not seem to be any collinearity, as the variance inflation factor (VIF) for all variables was typically below 5.

3. Results

We assumed a linear relationship between efficiency and temperature, and it is possible some of the complexities in the relationship between the two variables were lost. Rahman et al. found that the heat rate of a natural gas combustion EGU increased (and thus, efficiency decreased) fairly linearly with increasing ambient temperature [31]. Henry and Pratson, using the EPA and EIA datasets, also found a linear relationship between temperature and efficiency [16]. While it is possible that the relationship between temperature and EGU performance is nonlinear, Sathaye et al. argued that it is likely that nonlinear relationships occur at temperatures outside of current and future temperature projections [10].

The p-value of a regression model can be used to infer if there is indeed a relationship between the predictor (ambient temperature) and the response (efficiency), and a small p-value (usually 0.05 or less) indicates there is indeed an association between the two variables. The majority of EGUs (1220) have p-values that are less than 0.05, while 101 EGUs have p-values greater than 0.05. Of the 101 EGUs, 33 are natural gas combustion turbine units, 37 are coal steam units, 14 are natural gas steam units, and 17 are natural gas combined-cycle units. For the natural gas combustion turbine units, all 33 units have nameplate capacities below 200 MW. All coal and natural gas steam units with p-value >0.05 were installed before 1980 and most are cooled with once-through cooling systems. We were unable to identify a trend for natural gas combined-cycle units across nameplate capacity, installation year, climate zone, or number of data records per unit. For analyses of results onward, EGUs with a p-value above 0.05 will be excluded.

The effect of air temperature on EGU efficiency is inconsistent, as most generating units (872) experience a drop in efficiency due to rising temperatures, while other generating units (396) experience a rise in efficiency instead. While the median change in efficiency (regressing using all temperatures) for each cooling type is −0.01%/°C (Table A2), the range of responses for each cooling type varies. Results for dry-cooled generating units are the most consistent, having the smallest range of efficiency response (-0.05%/°C to +0.03%/°C), whereas generating units with once-through cooling (no ponds) and recirculating towers have the widest range of values (-0.09%/°C to +0.07%/°C).

Applying the regression model within temperature bins, dry-cooled generating units are likely to experience a greater reduction in efficiency per 1 °C increase in ambient temperature when temperatures are above average (i.e., above the 90th percentile) compared to when temperatures are average (i.e., between the 50th and 75th percentiles). The residual standard error values remain consistent when regressing all temperatures together versus regressing temperature bins (Fig. A4), indicating the accuracy of the regression models across temperature bins are relatively similar to one another. No distinguishable difference can be seen between coal steam and natural gas combined-cycle generating units that utilize dry cooling (Fig. A3). However, a visible difference can be seen when analyzing dry-cooled generating units across climate zones. In regions that are hot and arid, units with dry cooling are more likely to experience greater efficiency losses due to increasing ambient temperature (Fig. 4). At temperatures above the 90th percentile, the median change in efficiency for dry-cooled generating units located in Hot-Dry regions is −0.09%/°C. We expected dry-cooled generating units located in cold regions to be less negatively impacted by temperature increases, but our results show that these units are likely to experience similar decreases in efficiency (Fig. 4) as units located in Hot-Dry regions. Upon closer inspection, many EGUs in regions classified as Cold experience warmer temperatures of over 30 °C in the summer months (e.g., counties in Nevada and Utah), which can skew the results differentiated by climate zone when compared to counties that are typically more mild year-round.

The impacts of rising ambient temperature on the efficiency of wet-cooled electricity generating units are still inconclusive and inconsistent after regressing within temperature bins. For 225 generating units, a 1 °C increase in ambient temperature leads to increases in efficiency, even at temperatures above the 90th percentile or between the 75th and 90th percentiles. Of the 225 generating units, 66 are coal steam units with once-through cooling (no ponds), 45 are natural gas combustion units, 40 are coal steam units with recirculating tower cooling, and 25 are natural gas combined-cycle with recirculating tower cooling.

Similar to dry cooling systems, many generating units utilizing recirculating cooling towers experience greater efficiency losses when temperatures are above average (i.e., above the 90th percentile), but the results also span a wider range at higher temperatures. No significant trend can be found for recirculating tower-cooled generating units when further broken down by fuel and prime mover (Fig. A3) or climate zone (Fig. 4). For generating units with recirculating systems that have cooling ponds, the trend of more significant reductions in efficiency at higher than average temperatures cannot be seen.

No trends in efficiency changes due to ambient air temperature increase can be found for generating units with once-through cooling systems (with or without cooling ponds). The median change in efficiency per 1 °C increase in ambient temperature at higher than average temperatures (i.e., above the 90th percentile) does not vary much from the change in efficiency at average temperatures. Additionally, unlike generating units with recirculating cooling towers, the widest range of results for once-through cooled generating units do not occur at the highest temperature bin (above the 90th percentile). Instead, for once-through cooled generating units, the widest range of efficiency responses occur at ambient temperatures between the 50th and 75th percentiles.

Results for natural gas combustion turbines are mainly inconclusive and inconsistent. Distinguishing the regression across temperature bins does not have significant impacts on the results. Furthermore, there are no visible trends across climate zones (Fig. 4), nameplate capacity (Fig. A5), or installation year (Fig. A6).

4. Discussion

4.1. General implications

We observe discernible relationships between ambient temperature and power plant efficiency for dry-cooled generating units. Generating units utilizing dry cooling show a trend in decreasing efficiency with increasing ambient temperature, especially when temperatures are above average (i.e., above the 90th percentile). We also found that local climate plays a large role in determining the vulnerability of dry-cooled systems to temperature increases. The power plant that shows the most significant decrease in efficiency is the Chuck Lenzie Generating Station in Nevada; its two dry-cooled natural gas combined-cycle generating units experience a decrease of approximately −0.2%/°C (at temperatures above the 90th percentile). With increasing installations of dry cooling technologies, many of which in hot and arid regions, it is important to consider how these systems will be impacted by future climate change scenarios.

There are no other empirical analyses focusing on the impacts of ambient air temperature on the efficiency of dry-cooled generating units, so we can only compare our results of theoretical models. For natural gas combined-cycle units with dry cooling, at temperatures above the 90th percentile, the median change in efficiency at temperatures above the 90th percentile is −0.07%/°C with a range of −0.20%/°C to +0.05%/°C. Maulbetsch and DiFilippo found that at temperatures greater than 15 °C, natural gas combined-cycle units that are dry-cooled experience a 0.7% decrease in capacity per 1 °C increase in temperature [6]. While we cannot directly compare change in efficiency to change in capacity, our results are similar in magnitude in some cases and up to an order of magnitude less in others, depending on the generating unit, than the value obtained by Maulbetsch and DiFilippo [6].

The results obtained for wet-cooled generating units show that ambient temperature alone is not sufficient to predict the efficiency of electricity generating units. While we expected increasing ambient temperatures to result in decreasing generator efficiency, our results are mainly inconclusive. Additionally, at higher temperature bins (i.e., above the 90th percentile), the change in efficiency for generating units with recirculating cooling systems (with and without cooling ponds) span a wider range. Generating units with once-through cooling (with and without cooling ponds) do not indicate a strong or discernible relationship between generator efficiency and ambient air temperature.

Results for generating units utilizing wet cooling systems, while similar to previous empirical work, differ from thermodynamic and integrated models. Henry and Pratson found the impact of wet-bulb temperature on the efficiency of power plants with recirculating cooling towers to be approximately −0.06%/°C to +0.04%/°C [16], which reflects the range of values obtained from our regression at temperatures below the 50th percentile (−0.07%/°C to +0.08%/°C). However, for all other temperature bins, the resulting change in efficiency for generating units with recirculating cooling towers span a wider range of values. At temperatures above the 90th percentile, the change in efficiency ranges from −0.33%/°C to +0.21%/°C (Fig. 3). For natural gas combined-cycle units with recirculating cooling towers, at temperatures above the 90th percentile, the median efficiency change per 1 °C increase in ambient temperature is −0.06%/°C, with a range of −0.29%/°C to +0.16%/°C (Fig. A3). Our results are a magnitude of order greater than the results obtained by González-Díaz et al. [32] who found that the efficiency of one recirculating tower-cooled natural gas combined-cycle generating unit decreases from 50.95% to 48.01% when the temperature increases from 15 °C to 45 °C (equivalent to −0.098%/°C) [32]. Arrieta and Lora found that between temperatures 0–35 °C, the

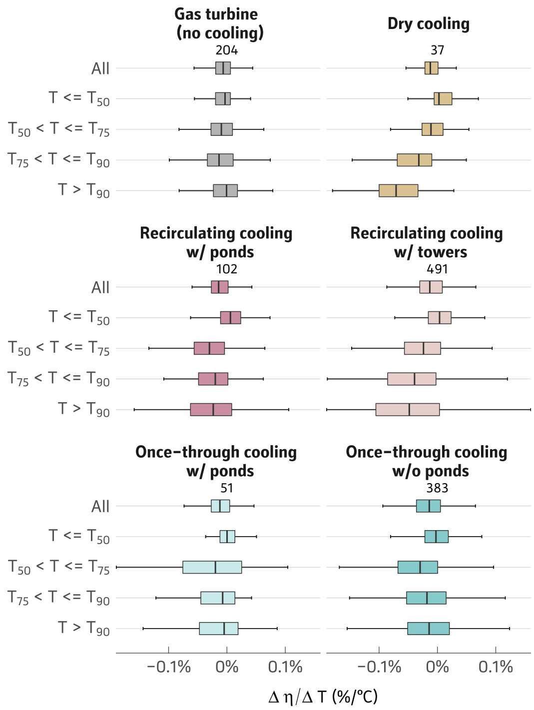

Fig. 3. Regression results for generating unit efficiency change per 1 °C increase in temperature ($\Delta\eta/\Delta T$), plotted and characterized by cooling system type. (Outliers are not included in box plots.) Dry-cooled systems experience the greatest decreases in efficiency due to rising temperatures. For generating units with recirculating cooling towers, wet-bulb temperature was used in the regression ($T = T_{wb}$). For all other cooling types and for natural gas combustion generators, dry bulb temperature was used in the regression ($T = T_{db}$). Subscripts on temperature variables on the y-axis refer to quartile bounds based on distributions of hourly temperatures.

net power of a 600 MW recirculating-cooled natural gas combined-cycle units decreases by 75 MW [33]. The only other study to our knowledge that has studied the impact of ambient air temperature on the efficiency of once-through-cooled generating units is by Henry and Pratson, who estimated the impact of temperature on the efficiency of once-through cooled power plants to be approximately −0.02%/°C to +0.05%/°C [16]. The results obtained from our analysis fall within a wider range, especially at higher temperatures (i.e., above the 90th percentile), where once-through cooled (no ponds) generating units can experience a change in efficiency from −0.16%/°C to +0.13%/°C. Our results have a greater range than the previous empirical analysis conducted by Henry and Pratson likely because of the greater sample size used and therefore a wider range of possible responses from the generating units.

Inconsistencies in responses in efficiency to rising air temperatures for wet-cooled generating units indicate that there are likely other variables which will influence the efficiency, especially at abnormally high temperatures. While recirculating cooling towers are tightly linked with the evaporative process, the efficiency of the generating unit is still dependent on streamflow variability as well [12]. The efficiencies of power plants with once-through cooling or recirculating cooling with a pond/reservoir are heavily dependent on the temperature of cooling water, since higher intake water temperatures are less effective in removing heat in thermoelectric plants [34]. As mentioned previously in the Results section, a large number of generating units whose efficiencies do not have strong relationships with ambient temperature (p-values greater than 0.05) are coal and natural gas steam generating units installed before 1980 (and primarily have once-through cooling systems). The cooling systems of power plants are often not as flexible in operation as their boilers and generators (i.e., while a generator can operate at partial load, its cooling system might still operate at full load) [35], and further, dry-bulb air temperature does not scale linearly with water temperature, which will matter more in terms of moderating power plant efficiency. Thus, particularly for older once-through cooled units with low capacity factors, the relationships between cooling water usage, generator efficiency, and ambient climatic conditions might be skewed [36,34].

Previous studies utilizing theoretical models estimated that the efficiencies of gas turbines decrease by approximately 0.08–0.1% per 1 °C increase in ambient air temperature [4,5], but the median efficiency change for natural gas combustion EGUs from our results is an order of magnitude smaller at approximately −0.01%/°C. Generally, increasing ambient temperatures should lead to decreases in the efficiencies of natural gas combustion generating units. We expected to see that natural gas combustion generating units in Hot-Dry regions experience more significant decreases in efficiency as temperature increases when compared to other climate zones. However, our analysis across climate zones was inconclusive, which we believe to be due to inlet air cooling technologies that reduce the temperature of the ambient air before it enters the compressor. Inlet cooling technologies are often installed at natural gas combustion turbines located in hot and arid regions to prevent decreases in efficiency from temperature rises [37,34].

4.2. Data limitations

Increased data availability opens up possibilities for applications of machine learning and artificial intelligence in developing energy models [38]. However, many issues persist in merging climate, water, and energy data datasets for integrated analyses [39]. Some data challenges include missing data, varying spatio-temporal resolutions between datasets, heterogeneity in the data, and non-uniformity in data collection standards [40]. Furthermore, applying machine learning techniques to energy, water, and climate data can prove to be difficult in the presence of incomplete datasets and outliers [40]. Many of these issues also impeded this investigation, particularly in regards to matching data across disparate datasets (e.g., due to erroneous or missing EGU identification numbers) and identifying outliers in the data.

It is possible to incorporate water temperature, water elevation, and streamflow data into a quantitative analysis, but attempting to utilize historical water data raises complications. Based on water stations provided the United States Geological Survey (USGS) and the Environmental Protection Agency, significant numbers of hourly readings of water temperature did not become available until recent years. Additionally, only a few water stations provide data at short enough distances upstream to power plants to be of value. Water temperature readings are also further complicated by other parameters such as streamflow and the depth at which sensors are located. The EIA Form 923 dataset provides self-reported values for water intake temperature at power plants [41], but these values are at the monthly level and their validity needs to be assessed. Studies that analyzed reported water withdrawal values from the same EIA Form 923 dataset found many inconsistent and unrealistic values [42–44].

Despite the exclusion of water availability and water temperature impacts in this analysis, we gained many insights on the state of electricity grid operations data. One of the biggest difficulties in working with both the EPA AMPD and EIA Form 860 datasets is the lack of consistencies in how generators and boilers are named, which makes it difficult to cross reference information between the databases. These inconsistencies have likely been major factors in preventing other large statistical analyses using these data. Almost all generator matching between the two datasets was done through pattern detection in R. However, there were a dozen or so units that had to be matched manually due to the fact that there was no discernible pattern between the two datasets to match the units. We were able to match over a thousand units, a larger sample size than previous studies utilizing the AMPD and EIA datasets by several orders of magnitude. We

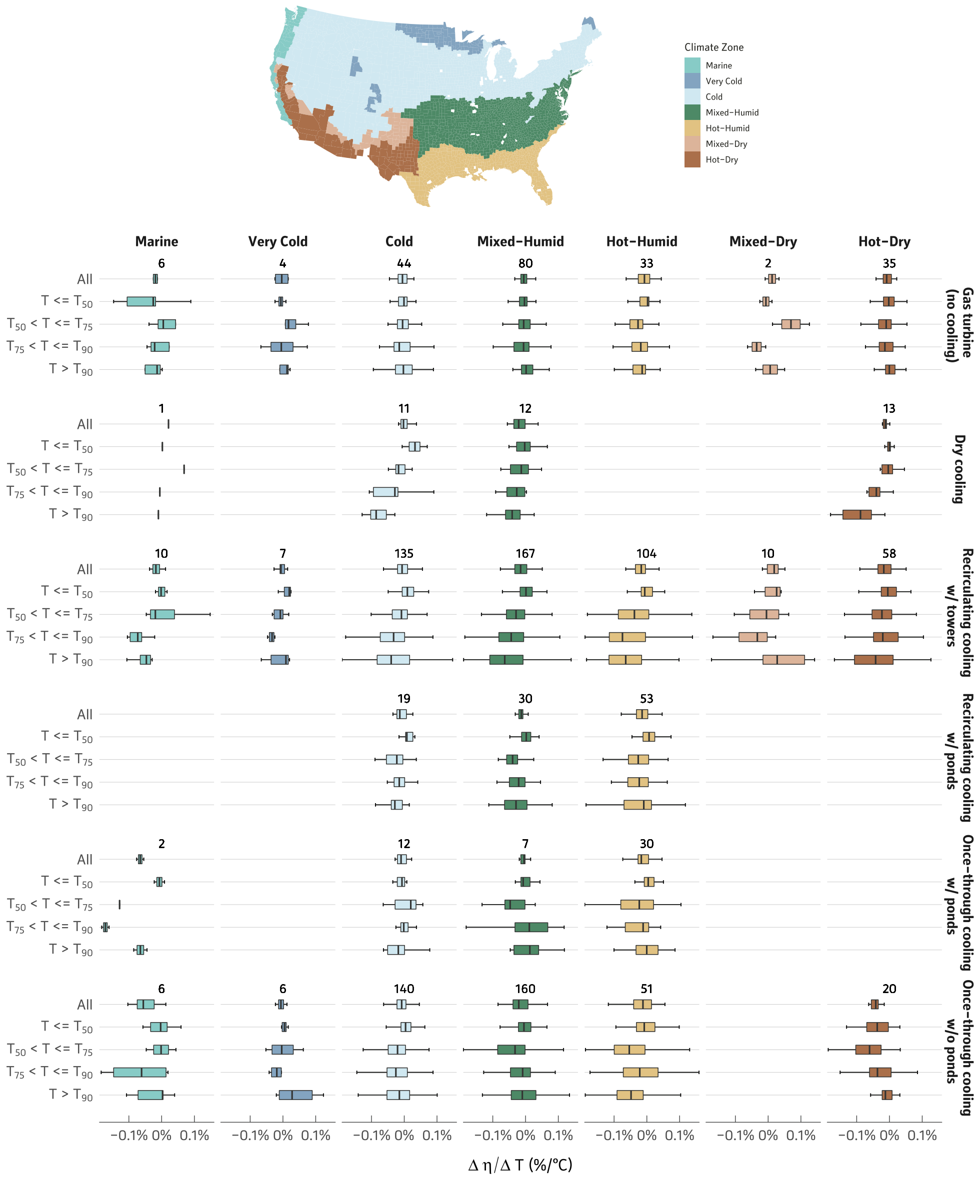

Fig. 4. Regression results for generating unit efficiency change per 1 °C increase in temperature ($\Delta\eta/\Delta T$), plotted and characterized by cooling system type and climate zone. (Outliers are not included in box plots.) The most extreme decreases in efficiency can be seen for dry-cooled generating units located in Hot-Dry regions. For generating units with recirculating cooling towers, wet-bulb temperature was used in the regression ($T = T_{wb}$). For all other cooling types and for natural gas combustion generators, dry bulb temperature was used in the regression ($T = T_{db}$).

acknowledge that there are likely a few units that were not matched properly, but we believe this to be a very small percentage.

The reporting of data was also inconsistent across the years analyzed. For example, many EGUs had unit codes and cooling system types that were missing in the earlier releases of the EIA Form 860 datasets, which made it difficult to properly match natural gas combined-cycle EGUs, as we were concerned with a single cooling *type* for the *unit* (not the generator). Because the reporting instructions for the AMPD database differed for earlier years [20], it is possible that power plant operators are not reporting data consistently across the span of the analysis (2008–2017). We tried to accommodate for this by doing most of our characterization of EGUs by year. Another issue with the EPA AMPD database is that steam generation is not reported for all natural gas combined-cycle EGUs. We believe many previous studies have been utilizing the AMPD reported load values without thoroughly considering or analyzing the quality of the data. While aggregating electricity generation to the plant level (as many previous studies have done) is sufficient in many contexts, plant-level aggregation can be a problem when analyzing differences in efficiency across technologies since many power plants use multiple fuels, prime movers, and cooling systems.

We matched each EGU to the nearest NOAA weather station (for each year in the study). Because we did not implement a filter for maximum distance, there might be discrepancies between the temperature reported at a weather station and the temperature at the actual EGU site. Furthermore, heat sources at power plants can raise the local temperature at the EGU site itself [28].

4.3. Implications for future work

Empirical analyses of electricity generation and climatic data can provide insights into how power systems have responded historically to changes in climate conditions, but insufficient available data make it difficult to accurately and extensively capture the impacts of climate conditions on power systems. The use of thermodynamic and/or integrated models, in conjunction with empirical data, can help (1) address quality and quantity issues in historical data and (2) improve understanding of the relationship between climatic variables and generator operations in the following ways:

- Climate: The inclusion of cooling water characteristics will provide a more robust understanding of the vulnerability of wet-cooled generating units to climate variability. Because current observational data available on streamflow, water quality, and water elevation are insufficient for a large scale analysis, modeling of cooling water characteristics could fill in existing data gaps.
- Operation: While sufficient data on operational variables such as capacity factor and ramping exist, the use of technologies such as inlet cooling will change how generating units perform under climate variability. Furthermore, the use of emissions control equipment can impact the net generation (and therefore efficiency) of an electricity generating unit. While the EIA Form 860 has information regarding pollution controls installed at U.S. power plants [17], the actual operations of emission control systems are not available.
- Regulation: While some permitting data are available, no information provides insight into which hours power plants modify operations to comply with regulations. For example, the Clean Water Act (CWA) Section 316(a) regulates variations in surface water temperature due to thermal effluent from power plants and requires power plants to curtail operations when either the discharge water temperature or the temperature difference between the intake and the discharge is too high [45]. With water availability projected to decrease and water temperatures projected to increase in many regions, accounting for curtailments related to regulated intake water temperatures and/or discharge water temperatures will be important in assessing the resiliency of the electricity grid [12].

5. Conclusions

As climate change is expected to increase temperatures in many areas across the country, the performance and reliability of the electricity grid will decrease. A regression model was developed and applied to a large set of EGUs to quantify the impact of ambient air temperature on generator efficiency over a 10 year period of time. The impacts were analyzed across varying fuel types, prime movers, cooling system types and climate regions. This study is the first to statistically analyze the impacts of climate and operational variables on generator efficiency with such a large sample size. While previous studies focused on dozens of generators at most, this analysis included over one thousand electricity generating units (618 unique power plants).

Results indicate that while air temperature alone is insufficient to capture the relationship between generators using wet cooling technologies, dry-cooled generating units can experience a decrease in efficiency of up to 0.2% per 1 °C increase in ambient temperature, especially in areas that are hot and arid. As the number of dry-cooled power plants will likely continue to grow into the future, the potential impact of the vulnerability of these power plants to climate variability and climate change could be significant. Results regarding the efficiency losses of natural gas combustion turbines, which do not utilize water-cooled or air-cooled condensers for electricity generation, were also inconclusive. The use of inlet cooling technologies, which are commonly installed at natural gas combustion units in hot regions to improve generator performance on hot days, likely distorted the relationship between generator efficiency and temperature in this analysis.

We also believe the insights acquired on the state of power plant operations data are useful for the scientific community. We suggest that authors who plan to use the EPA CEMS data do so with caution, particularly for natural gas combined-cycle units because both steam and gas generation are not always reported. Although we present a method for identifying whether or not generation from the entire natural gas combined-cycle unit is reported, there is no perfect solution. For the EIA dataset, we recommend checking for inconsistencies between recent and older years when attempting to do multi-year analyses. These issues were compounded by the fact that there are many inconsistencies in how generators are named in the EPA and EIA datasets. Despite these data challenges, there is a great deal of merit to these datasets when meticulous care is taken in the interpretation and analyses processes.

Acknowledgements

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Appendix A. Methods

A.1. Data filtering

Table A1.

Table A1
Lower and upper limits placed on heat rates, based on the Environmental Protection Agency's assumptions for the Power Sector Modeling Platform [19].

Unit Type	Nameplate Capacity	Lower Heat Rate Limit (Btu/KWh)	Upper Heat Rate Limit (Btu/KWh)
CL-ST	All	8,300	14,500
NG-ST	All	8,300	14,500
NG-GT	> = 80 MW	8,700	18,700
NG-GT	< 80 MW	8,700	36,800
NG-CC	All	5,500	15,000

A.2. Final set of units

Figs. A1 and A2.

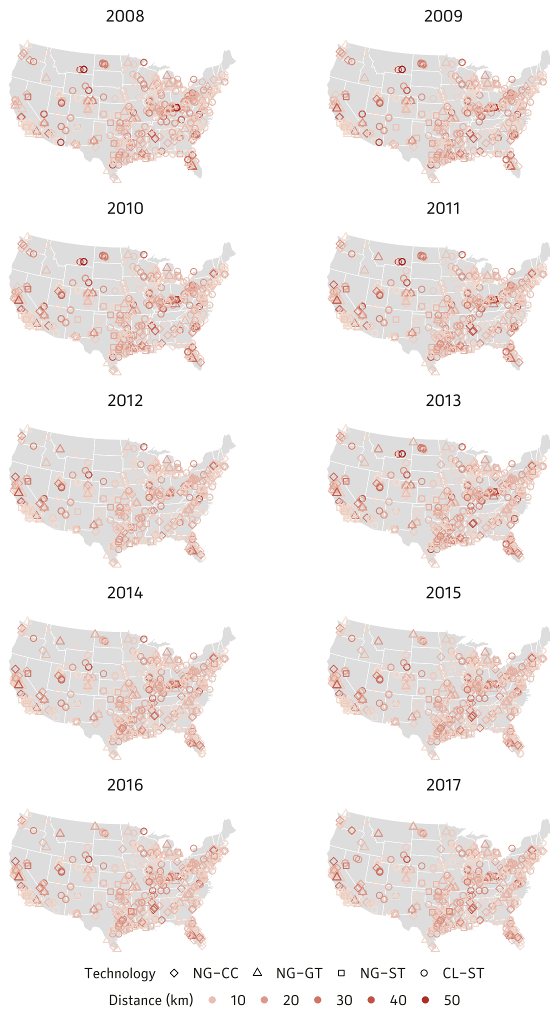

Fig. A1. Generating units analyzed in each year are mapped and characterized by distance to nearest NOAA weather station.

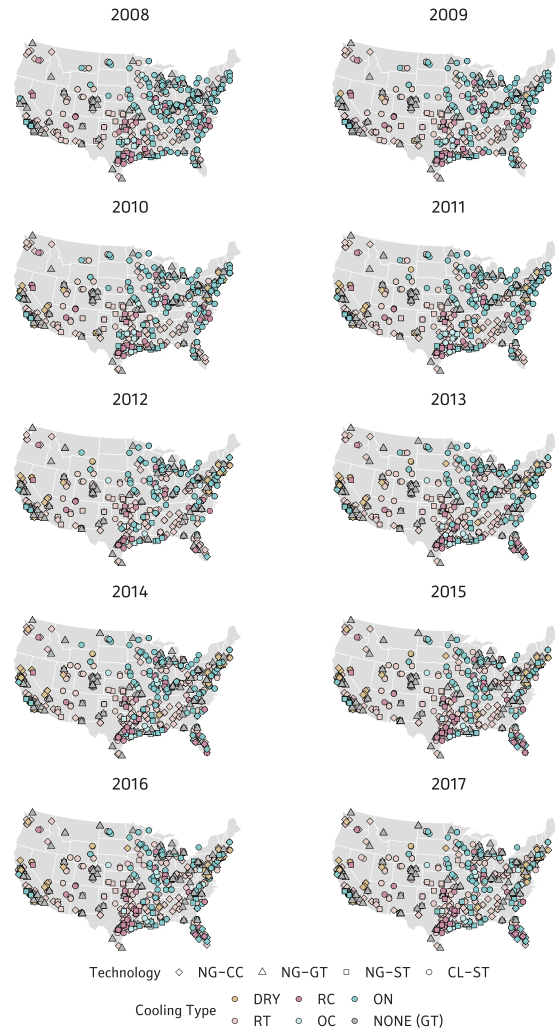

Fig. A2. Generating units analyzed in each year are mapped and characterized by fuel, prime mover, and cooling system type.

Appendix B. Results

Table A2.
Figs. A3–A6.

Table A2
Changes in efficiency per 1 °C increase in ambient air temperature, differentiated by cooling type: NONE (no cooling, for natural gas combustion generators), RT (recirculating cooling with tower), DRY (dry cooling), RC (recirculating with cooling pond), OC (once-through with cooling pond), and ON (once-through without cooling pond). The statistical summaries provided are: Min (minimum), Q25 (25th percentile), Med (median), Q75 (75th percentile), and Max (maximum).

			$\Delta\eta/\Delta T_{wb}$ (%/°C)				
Cooling Type	Temperature Break Category	# of EGUs	Min	Q25	Med	Q75	Max
RT	All	491	−0.09%	−0.03%	−0.01%	0.01%	0.07%
RT	$T_{wb} <= T_{wb,50}$	491	−0.07%	−0.02%	0.004%	0.02%	0.08%
RT	$T_{wb,50} < T_{wb} <= T_{wb,75}$	491	−0.15%	−0.06%	−0.02%	0.01%	0.10%
RT	$T_{wb,75} < T_{wb} <= T_{wb,90}$	491	−0.23%	−0.09%	−0.04%	0.001%	0.14%
RT	$T_{wb} > T_{wb,90}$	491	−0.33%	−0.12%	−0.06%	0.01%	0.21%
			$\Delta\eta/\Delta T_{db}$ (%/°C)				
			Min	Q25	Med	Q75	Max
DRY	All	37	−0.05%	−0.02%	−0.01%	0.001%	0.03%
DRY	$T_{db} <= T_{db,50}$	37	−0.05%	−0.01%	0.003%	0.02%	0.07%
DRY	$T_{db,50} < T_{db} <= T_{db,75}$	37	−0.08%	−0.03%	−0.01%	0.01%	0.05%
DRY	$T_{db,75} < T_{db} <= T_{db,90}$	37	−0.15%	−0.07%	−0.03%	−0.01%	0.05%
DRY	$T_{db} > T_{db,90}$	37	−0.20%	−0.11%	−0.07%	−0.03%	0.03%
RC	All	102	−0.06%	−0.03%	−0.01%	0.002%	0.04%
RC	$T_{db} <= T_{db,50}$	102	−0.06%	−0.01%	0.01%	0.02%	0.07%
RC	$T_{db,50} < T_{db} <= T_{db,75}$	102	−0.13%	−0.06%	−0.03%	0.002%	0.06%
RC	$T_{db,75} < T_{db} <= T_{db,90}$	102	−0.11%	−0.05%	−0.02%	0.003%	0.06%
RC	$T_{db} > T_{db,90}$	102	−0.16%	−0.06%	−0.02%	0.01%	0.12%
OC	All	51	−0.07%	−0.03%	−0.01%	0.005%	0.05%
OC	$T_{db} <= T_{db,50}$	51	−0.04%	−0.01%	0.0002%	0.01%	0.05%
OC	$T_{db,50} < T_{db} <= T_{db,75}$	51	−0.19%	−0.08%	−0.02%	0.03%	0.10%
OC	$T_{db,75} < T_{db} <= T_{db,90}$	51	−0.16%	−0.06%	−0.01%	0.02%	0.12%
OC	$T_{db} > T_{db,90}$	51	−0.14%	−0.05%	−0.01%	0.02%	0.12%
ON	All	383	−0.09%	−0.04%	−0.01%	0.01%	0.07%
ON	$T_{db} <= T_{db,50}$	383	−0.08%	−0.02%	−0.003%	0.02%	0.08%
ON	$T_{db,50} < T_{db} <= T_{db,75}$	383	−0.19%	−0.08%	−0.03%	0.001%	0.12%
ON	$T_{db,75} < T_{db} <= T_{db,90}$	383	−0.16%	−0.06%	−0.02%	0.02%	0.12%
ON	$T_{db} > T_{db,90}$	383	−0.16%	−0.05%	−0.01%	0.02%	0.13%
NONE (GT)	All	204	−0.06%	−0.02%	−0.01%	0.01%	0.04%
NONE (GT)	$T_{db} <= T_{db,50}$	204	−0.06%	−0.02%	−0.003%	0.01%	0.04%
NONE (GT)	$T_{db,50} < T_{db} <= T_{db,75}$	204	−0.08%	−0.03%	−0.01%	0.01%	0.07%
NONE (GT)	$T_{db,75} < T_{db} <= T_{db,90}$	204	−0.10%	−0.03%	−0.01%	0.01%	0.08%
NONE (GT)	$T_{db} > T_{db,90}$	204	−0.09%	−0.02%	−0.001%	0.02%	0.08%

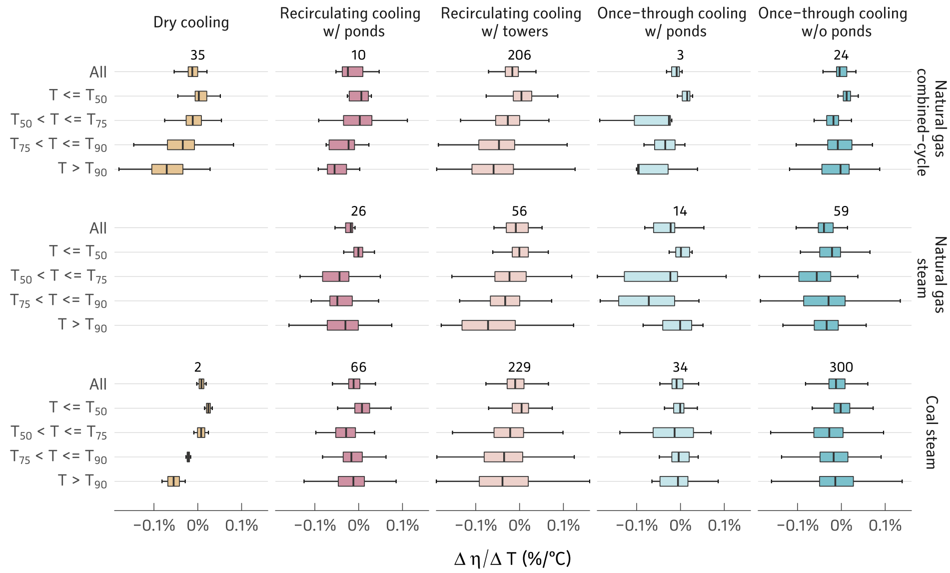

Fig. A3. Regression results for generating unit efficiency change per 1 °C increase in temperature ($\Delta\eta/\Delta T$), plotted and characterized by fuel, prime mover, and cooling system type. (Outliers are not included in box plots.) For generating units with recirculating cooling towers, wet-bulb temperature was used in the regression ($T = T_{wb}$). For all other cooling types and for natural gas combustion generators, dry bulb temperature was used in the regression ($T = T_{db}$).

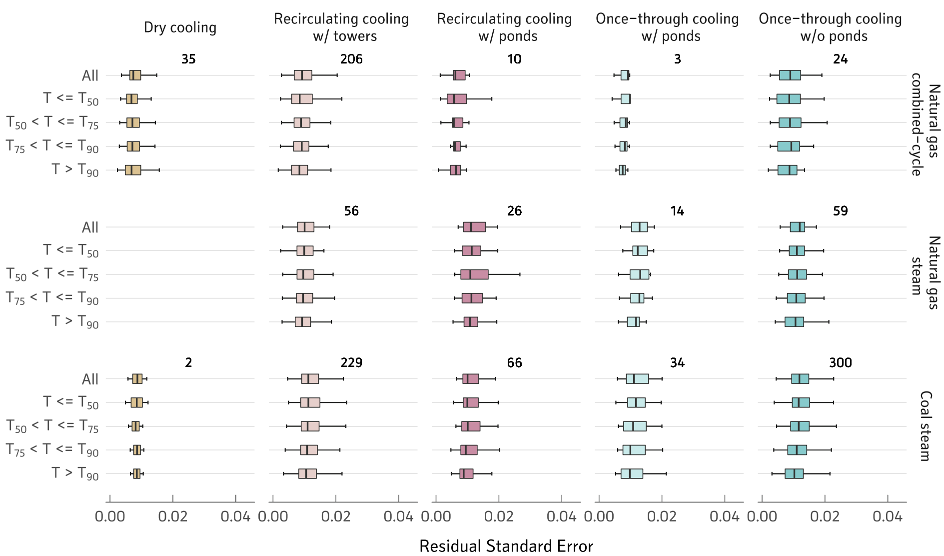

Fig. A4. Residual standard error (RSE) values from regression models, plotted and characterized by fuel, prime mover, and cooling type. Note that in this regression model, modeling is not split by temperature categories. (Outliers are not included in box plots.) For generating units with recirculating cooling towers, wet-bulb temperature was used in the regression ($T = T_{wb}$). For all other cooling types and for natural gas combustion generators, dry bulb temperature was used in the regression ($T = T_{db}$).

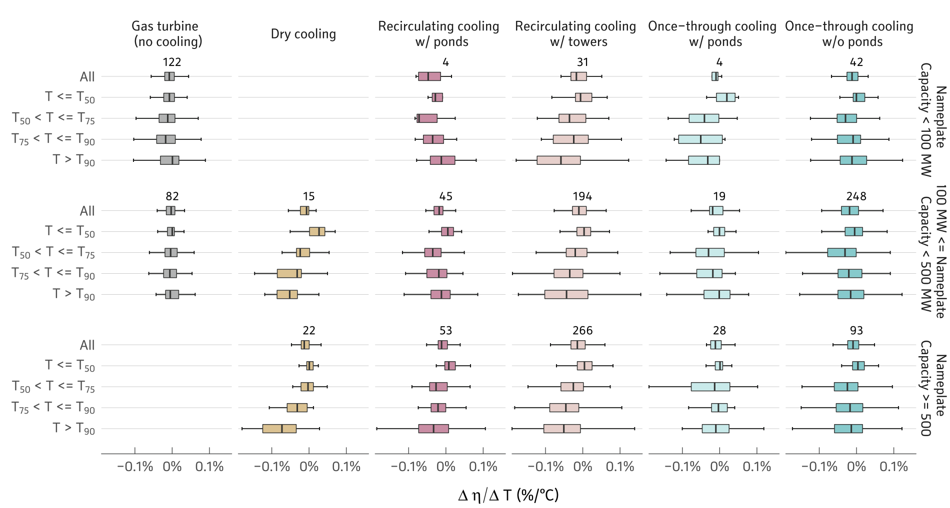

Fig. A5. Regression results for generating unit efficiency change per 1 °C increase in temperature ($\Delta\eta/\Delta T$), plotted and characterized by cooling system type and nameplate capacity. (Outliers are not included in box plots.) For generating units with recirculating cooling towers, wet-bulb temperature was used in the regression ($T = T_{wb}$). For all other cooling types and for natural gas combustion generators, dry bulb temperature was used in the regression ($T = T_{db}$).

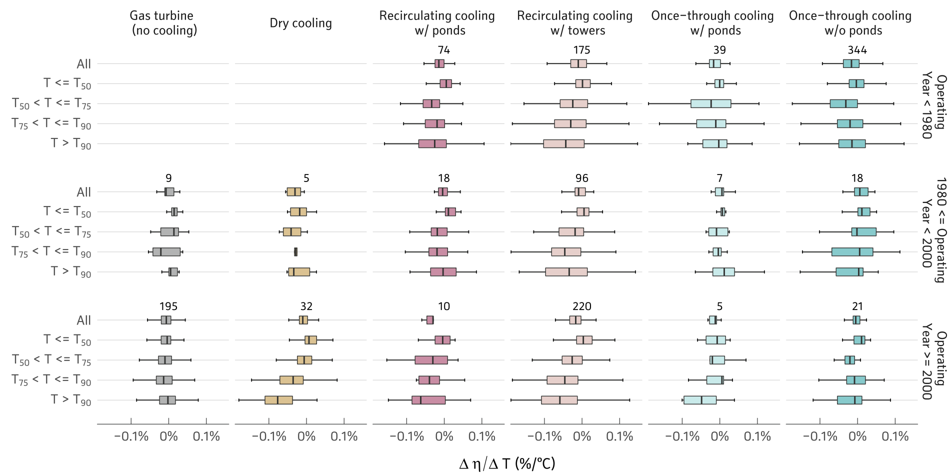

Fig. A6. Regression results for generating unit efficiency change per 1 °C increase in temperature ($\Delta\eta/\Delta T$), plotted and characterized by cooling system type and generating unit operation year. (Outliers are not included in box plots.) For generating units with recirculating cooling towers, wet-bulb temperature was used in the regression ($T = T_{wb}$). For all other cooling types and for natural gas combustion generators, dry bulb temperature was used in the regression ($T = T_{db}$).

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