

LETTER • OPEN ACCESS

The role of humidity in determining future electricity demand in the southeastern United States

To cite this article: Deeksha Rastogi *et al* 2021 *Environ. Res. Lett.* **16** 114017

View the [article online](#) for updates and enhancements.

You may also like

- [The role of temperature in the variability and extremes of electricity and gas demand in Great Britain](#)
H E Thornton, B J Hoskins and A A Scaife
- [The relationship between wind power, electricity demand and winter weather patterns in Great Britain](#)
Hazel E Thornton, Adam A Scaife, Brian J Hoskins et al.
- [Spectral signatures of non-thermal baths in quantum thermalization](#)
Ricardo Román-Ancheyta, Bar Çakmak and Özgür E Müstecaplıolu

ENVIRONMENTAL RESEARCH
LETTERS

LETTER

The role of humidity in determining future electricity demand in the southeastern United States

OPEN ACCESS

RECEIVED
2 August 2021REVISED
7 October 2021ACCEPTED FOR PUBLICATION
14 October 2021PUBLISHED
26 October 2021

Original content from this work may be used under the terms of the [Creative Commons Attribution 4.0 licence](#).

Any further distribution of this work must maintain attribution to the author(s) and the title of the work, journal citation and DOI.

Deeksha Rastogi^{1,*} , Flavio Lehner^{2,3} , Teja Kuruganti¹ , Katherine J Evans¹ , Kuldeep Kurte¹ and Jibonananda Sanyal¹ ¹ Computational Sciences and Engineering Division, Oak Ridge National Laboratory, Oak Ridge, TN, 37831, United States of America² Department of Earth and Atmospheric Sciences, Cornell University, Ithaca, NY, 14853, United States of America³ Climate and Global Dynamics Laboratory, National Center for Atmospheric Research, Boulder, CO, 80305, United States of America

* Author to whom any correspondence should be addressed.

E-mail: rastogid@ornl.gov**Keywords:** relative humidity, heat stress, climate change, high resolution, electricity demandSupplementary material for this article is available [online](#)**Abstract**

Co-occurrence of high relative humidity levels and high temperatures can increase human discomfort, thereby affecting electricity requirements for space cooling. While relative humidity is generally projected to decrease over land in a warming climate, the combined impact of warming and changes in humidity on heat stress, and thus electricity demand, are less clear. To evaluate the role of relative humidity in determining future electricity demand, we first develop predictive models based, separately, on temperature (T) and a heat stress index (apparent temperature (AT)) at an hourly scale using meteorological reanalysis data and electricity load from the United States Energy Information Administration over the four electricity regions in the southeastern United States. The AT model performs better than the T model in the historical period. We then apply the predictive models to a set of high-resolution climate projections to understand the role of relative humidity in determining the electricity demand in a warmer climate. Due to the nonlinear behavior of heat stress with warming, future electricity demand is substantially larger when estimated from AT than from T. The increase in demand projected by AT ranges between 16%–29%, 20%–33%, 14%–32% and 13%–26% and that by T model ranges between 12%–19%, 15%–19%, 14%–22% and 12%–20% over Southeast, Florida, Carolina, and Tennessee respectively. This amplification of electricity demand by humidity is strongest for the highest temperature quantiles, but also occurs at moderate future temperatures that coincide with elevated relative humidity episodes, emphasizing the importance of considering humidity in future heat stress and electricity demand assessments.

1. Introduction

Accurate estimation of electricity demand is crucial for short term decision making to effectively balance demand and supply as well as for long-term planning to ensure a resilient and sustainable power infrastructure. A warming climate is posing additional strain on the electric grid by modifying demand patterns and increasing risks of power outages, primarily associated with climate extreme events. Increases in intensity, frequency, and duration of climate extremes, e.g. heatwaves, is causing frequent and unanticipated disruptions, making

the electricity demand estimation not only more important but increasingly challenging. The estimation of electricity demand in response to these changes is needed at high temporal resolution to ensure adequate balancing during the peak hours, managing demand and facilitating high penetration of renewables. Thus far, numerous studies have modeled the impact of changing temperature on the electricity demand (Auffhammer *et al* 2017, Fonseca *et al* 2019, Rastogi *et al* 2019). These studies project a robust increase in electricity demand owing to enhanced space cooling requirements. However, most of these studies are restricted to temperature

or temperature-based measures of cooling demand, e.g. cooling degree days as the dependent variable and do not consider humidity in electricity demand modeling. Heat stress, which is caused by coinciding high relative humidity levels and high temperatures, increases human discomfort by decreasing heat tolerance due to human body's reduced ability for evaporative cooling, emphasizing its importance in determining electricity demand (Rastogi *et al* 2020, Sherwood and Huber 2010). For example, in humid regions such as southeastern United States (hereafter US), where high heat stress levels can increase the general and peak electricity demand, the use of temperature-only predictive models can lead to an underestimation of demand.

The continental land areas are warming at a higher rate as compared to the oceans, resulting in an enhanced moisture holding capacity of the near-surface atmosphere. While this results in an increase in specific humidity, relative humidity is generally decreasing over most of the land areas owing to limited moisture transport and lower evapotranspiration due to soil moisture depletion (Byrne and O'Gorman 2018). Moreover, during the hottest days, even specific humidity has been shown to decrease over the past seven decades in the Southwest and parts of Southeast US (McKinnon *et al* 2021). The drying during the hottest days has also been projected in a warmer climate over North America (Coffel *et al* 2019). Even though these changes in humidity may dampen the rise in humid-heat on the extreme hot days, the overall heat stress is projected to continue to increase in a warming climate (Buzan and Huber 2020). Given the changing roles of temperature and relative humidity in a warmer climate, it is even more important to understand their impact on human discomfort, which in turn will have important implications for future electricity demand.

Recently, a few studies have investigated the role of humidity in determining electricity demand by incorporating humidity-based indices along with temperature in the electricity demand estimation modeling (Maia-Silva *et al* 2020, Kumar *et al* 2020, Wang and Bielicki 2018). These studies emphasize that temperature-only models tend to underestimate electricity demand today and in a warmer climate. However, these studies are either limited by the temporal scale of analysis or the regional coverage. For instance, Maia-Silva *et al* (2020) evaluate the impact of heat stress indices over the conterminous US, their reliance on monthly data provides insights on the importance of humidity in driving the electricity demand but prevents an evaluation at time scales of occurrence of extreme events (e.g. hourly to daily). Heat waves can occur on a daily scale, and the role of humidity, temperature and demand vary based on the time of the day. Kumar *et al* (2020) and Wang and Bielicki (2018) use daily and hourly scale data but focused only on California and Northeastern

US respectively. The role of humidity in determining electricity demand over the Southeast, one of the most humid regions in the US, is not yet fully understood. The average annual temperature over the region has increased by approximately 2 °F since 1970. Moreover, an increase of 4 °F to 8 °F in annual temperature as well as an increase in the days above 95 °F is projected by the end of century. These projected changes in mean and extreme temperature along with high humidity levels in the region will result in an increase in heat stress (Weatherly and Rosenbaum 2017).

Therefore, it is critical to fill the gaps in our understanding of how heat stress and electricity demand covary and change with warming over the Southeast. Here, we develop statistical models that predict electricity demand based on temperature and a heat stress index that includes humidity at hourly scale, using meteorological data from the fifth generation European Centre for Medium-Range Weather Forecasts (ERA-5) reanalysis and electricity load from the US Energy Information Administration (EIA) over the four electricity regions in the Southeast. We then apply these models to high resolution climate model projections, dynamically downscaled to 4 km, to assess the impact of humidity on current and future electricity demand.

1.1. Data and methodology

1.1.1. Data

1.1.1.1. Electricity demand data

We use regional scale hourly electricity demand from the US Energy Information Administration (EIA) available from July 2015 to present for the four EIA electricity regions in the southeastern US, namely: (a) Tennessee, which primarily includes Tennessee along with parts of Mississippi, Alabama, Georgia, and Kentucky, (b) South Carolina and North Carolina (Carolinas), (c) Southeast, which includes Alabama, Georgia and parts of Mississippi and Florida, and (d) Florida (figures 1(a) and (b)).

1.1.1.2. Climate data

1.1.1.2.1. Observations

ERA5 reanalysis provides global hourly estimates of climate variables from 1979 to 2019 at a 31 km horizontal grid by assimilating historical observations with model estimates (Hersbach *et al* 2020). We obtain hourly estimates for temperature (T), dew point temperature, and surface pressure from ERA5 reanalysis, which we use to derive relative humidity. Apparent temperature (AT) is calculated using T and relative humidity following the National Oceanic and Atmospheric Administration (NOAA) heat index equation (equation (1)). Additional adjustments for different ranges of T and relative humidity are applied as detailed in the NOAA factsheet: www.wpc.ncep.noaa.gov/html/heatindex_equation.shtml. The equation provides AT

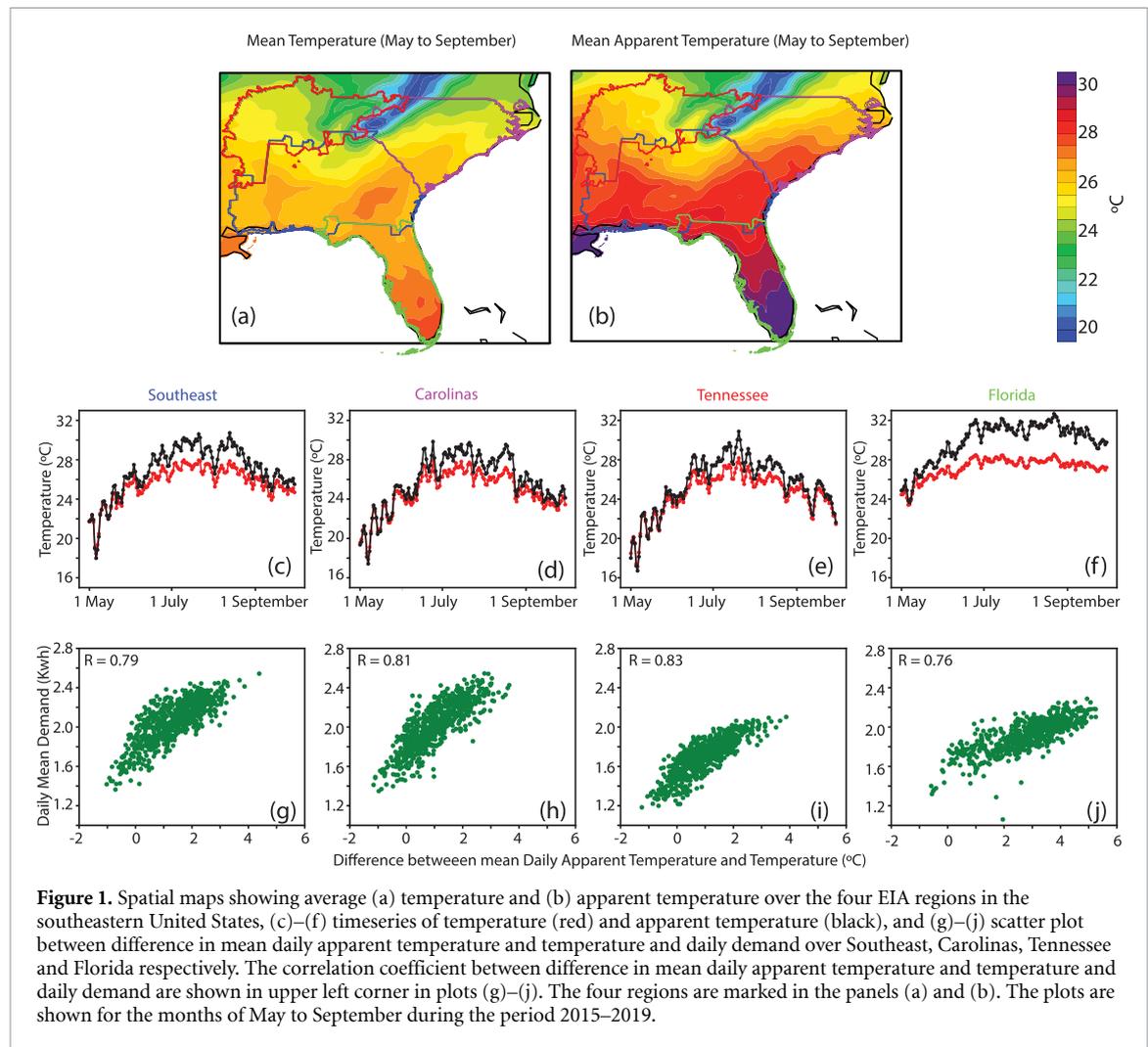


Figure 1. Spatial maps showing average (a) temperature and (b) apparent temperature over the four EIA regions in the southeastern United States, (c)–(f) timeseries of temperature (red) and apparent temperature (black), and (g)–(j) scatter plot between difference in mean daily apparent temperature and temperature and daily demand over Southeast, Carolinas, Tennessee and Florida respectively. The correlation coefficient between difference in mean daily apparent temperature and temperature and daily demand are shown in upper left corner in plots (g)–(j). The four regions are marked in the panels (a) and (b). The plots are shown for the months of May to September during the period 2015–2019.

in degree Fahrenheit (°F) which is converted to degree Celsius (°C) for further analysis. Finally, we calculate population weighted T and AT for each of the four selected EIA regions:

$$AT = c_1 + c_2T + c_3R + c_4TR + c_5T^2 + c_6R^2 + c_7T^2R + c_8TR^2 + c_9T^2R^2 \quad (5)$$

where

AT is the apparent temperature in °F.

T is the temperature in °F.

R is the in relative humidity in % between 0 and 100.

1.1.3.2. Model simulations

We use a set of high-resolution Weather Research Forecasting (WRF) model Version 3.4.1 (Skamarock *et al* 2008) simulations conducted at 4 km horizontal grid spacing (1360 × 1016 longitude-latitude grid points) with 51 vertical levels over a domain covering the conterminous US and parts of Canada and Mexico Liu *et al* 2017). Each WRF simulation extends from 1 October 2000 to 30 September 2013. The control simulation (CTRL) is driven by six hourly 0.7° ERA-Interim data (Dee *et al* 2011)

whereas the climate change experiment follows the pseudo global warming (PGW) approach, which is driven by modified ERA-Interim boundary forcing that includes a climate perturbation based on the climate change signal (2071–2100 minus 1976–2005) from 19 Coupled Model Intercomparison Project Phase 5 multi-model ensemble mean under the representative concentration pathway 8.5. The perturbed variables include horizontal wind fields, geopotential, temperature, specific humidity, soil temperature, sea surface temperature, sea level pressure and sea ice. Overall, the dominant climate change signal is a general warming and moistening of the atmosphere, whereas circulation changes are minimal. Within the domain, these simulations use spectral nudging towards ERA-Interim for the scales on the order of 2000 km and greater, reproducing present-day specific synoptic weather events both in the control and perturbed simulations Liu *et al* 2017). Therefore, the simulations highlight future thermodynamically driven changes. We obtain hourly temperature, specific humidity, and surface pressure from these simulations, which we use to derive relative humidity and AT. The relative humidity is calculated using the NCAR command language function

relhum_ttd that is based on the algorithm detailed in Dutton (1976).

1.2. Methodology

According to the US EIA, the total hourly energy load in the US is highest in the summer months. During the summer months, the energy consumption in residential and commercial buildings increases, mostly due to the high air-conditioning usage, which is used in 87% of homes in the US as per the US EIA Residential Energy Consumption Survey (Residential Energy Consumption Survey (RECS) 2009). Households and businesses increase the air conditioning utilization during hot days, which leads to peak demand. The daily electricity consumption (demand) follows the daily electricity usage habits for typical building occupants. Moreover, this daily energy consumption pattern is different during weekends and holidays than on weekdays.

We develop predictive models by establishing a linear statistical relationship between average per capita demand and cooling degrees based on population weighted: (a) T, and (b) AT for each of the four regions (figure S1 available online at stacks.iop.org/ERL/16/114017/mmedia). The cooling degrees for each hour are calculated as the deviation of T/AT from a 65 °F (18.3 °C) threshold. This threshold has been commonly used to calculate cooling degrees over the US (Petri and Caldeira 2015). Further, to capture the correlations of the energy demand with various time-related variables, we use hour of the day, day of the week and month as categorical variables in the predictive models. Thus, we represent the hourly per capita electricity demand (y) as,

$$y = a \times CD_T \text{ (or } CD_{AT}) + b \times \text{tod} + c \times \text{month} + d \times \text{dow} + \delta \quad (2)$$

where CD_T/CD_{AT} is hourly cooling degrees calculated based on T/AT in degrees Celsius, tod, month, and dow refer to categorical variables for time of the day, month of the year, and day of the week, and δ is constant.

We develop the models using data for the years 2015–2019, for which both ERA-5 meteorological data and US EIA electricity data are available. We train the models for the months of May–September during which space cooling is prominently used in the Southeast. We use ten-fold cross validation to train and test the models, and to evaluate the performance of the models. Once established, we use the complete dataset to develop the final set of statistical models and apply them to climate data from CTRL and PGW to estimate the historical and projected future electricity demand. We use population weighted T and AT from the set of climate simulations. To isolate the role of humidity on electricity demand, we assume other factors, including socioeconomic and technological, remain unchanged for the period of analysis.

We use the two sample Kolmogorov–Smirnov (K–S) test for the statistical significance of the difference in the demand distributions estimated by T versus AT in future periods at 5% significance level across all the four regions. The two sample K–S test is a non-parametric goodness-of-fit test that is used to compare two samples of probability distributions by quantifying the distance between the distributions (Massey 1951).

2. Results

2.1. Importance of incorporating humidity in electricity demand modeling

AT, a measure of human discomfort, has evidently higher values as compared to the T over the inherently humid southeastern US. The differences between mean daily AT and T are largest over Florida (up to 5.3 °C), followed by parts of the Southeast (up to 4.4 °C) particularly during the months of July and August whereas the differences over Carolinas and Tennessee range up to 3.7 °C and 3.9 °C respectively (figure 1). This reflects the magnifying power of relative humidity on heat stress in these humid regions and emphasizes the importance of incorporating humidity in addition to temperature for adequately accounting for heat stress-driven human discomfort. Moreover, as the daily mean difference between the AT and T increases, the daily mean electricity demand also increases, underscoring the importance of relative humidity in electricity demand modeling (figures 1(g)–(i)). The predictive models for each of the four regions using cooling degrees based on: (a) T, and (b) AT exhibit excellent fit with R^2 values ranging between 0.94–0.95 and 0.95–0.96 across the four regions for the two models respectively (table S1). We apply the ten-fold cross validation and find that the AT model performs better than the T model for the average out-of-fold predictions both in terms of R^2 as well as root mean square error (RMSE) across all the four regions. The AT model improves the RMSE as compared to the T model by 9.5%, 11.2%, 9.6%, and 6.8% for Southeast, Carolinas, Tennessee, and Florida respectively (table S1).

2.2. Role of humidity in determining future electricity demand

Despite a decrease in relative humidity, both the AT as well as the differences between the AT and T are projected to increase with future warming (figures 2 and S2). The WRF model projects increases in daily mean T and AT that range between 3.4 °C–6.0 °C and 4.7 °C–11.0 °C over the four regions during May–September for the 13 years (figure S3). This is in part due to the fact that at similar or lower humidity, the magnifying power of humidity increases with increasing T, i.e. similar or lower relative humidity levels will still cause greater human discomfort at higher temperatures. Consequently, in

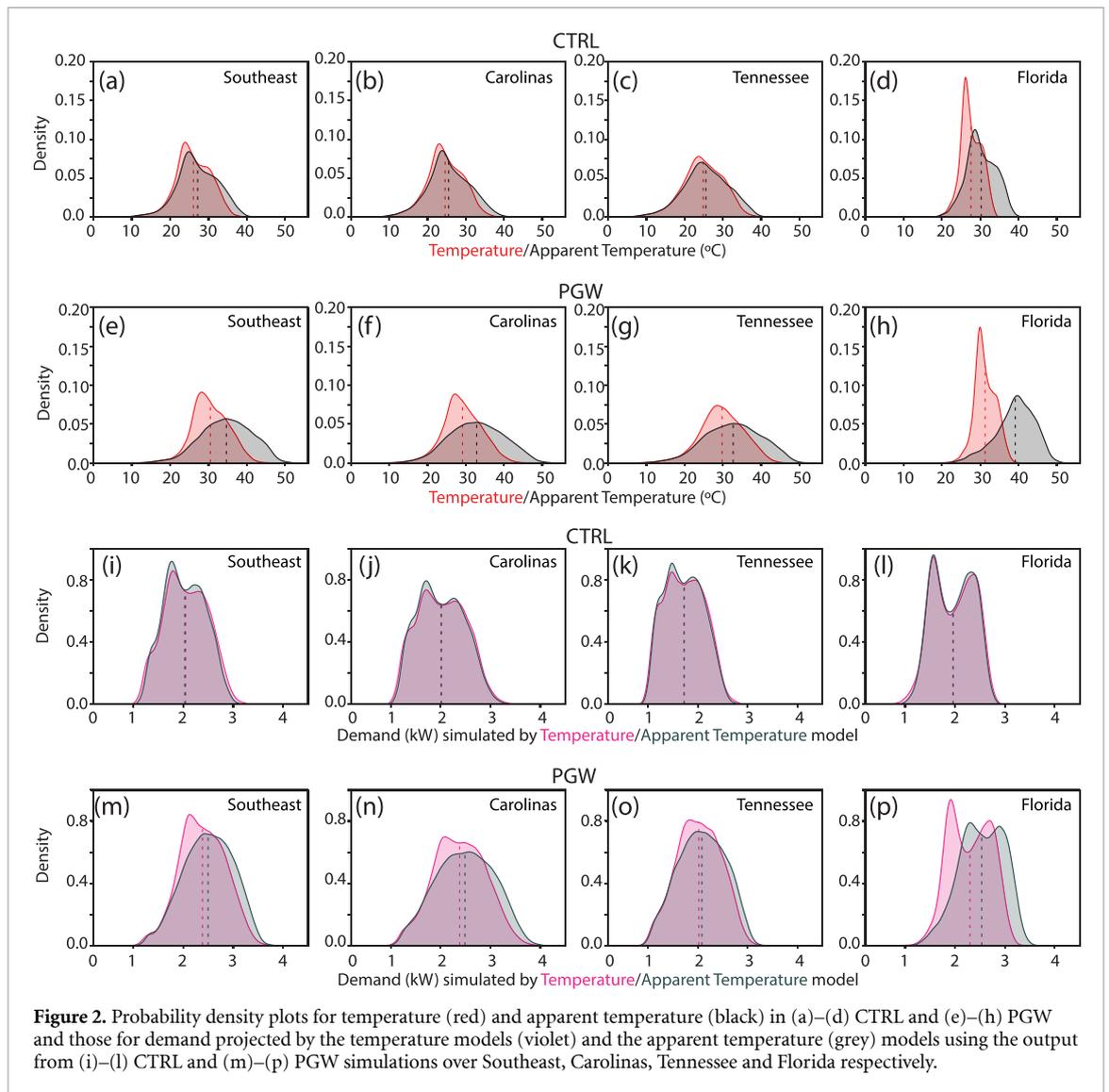
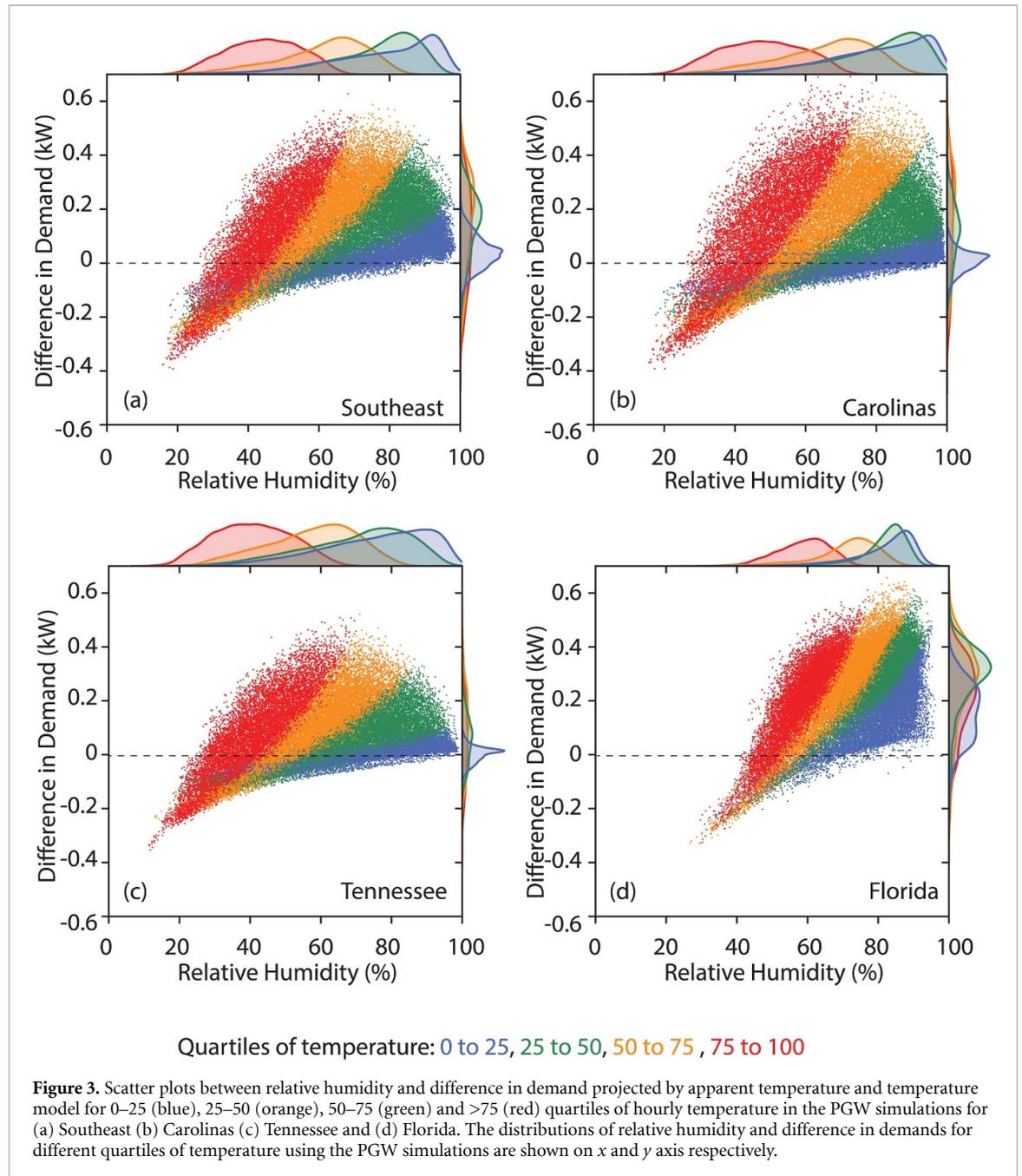


Figure 2. Probability density plots for temperature (red) and apparent temperature (black) in (a)–(d) CTRL and (e)–(h) PGW and those for demand projected by the temperature models (violet) and the apparent temperature (grey) models using the output from (i)–(l) CTRL and (m)–(p) PGW simulations over Southeast, Carolinas, Tennessee and Florida respectively.

a warmer climate, not only is the electricity demand projected to increase by both the T and AT models, but the AT model projects a significantly larger increase as compared to the T model (figures 2(m)–(p) and S2(m)–(t)). The T model project increases in daily mean demand that range between 12%–19%, 15%–19%, 14%–22% and 12%–20% whereas AT model project increases that range from 16%–29%, 20%–33%, 14%–32% and 13%–26% over Southeast, Florida, Carolina, and Tennessee respectively across May–September for the 13 years (figure S3). To further understand the role of humidity in determining future electricity demand, we bin the data into quartiles of the hourly temperature distribution (0–25, 25–50, 50–75 and 75–100 percentiles) in PGW and plot relative humidity against the difference in demand between AT and T models for each of these percentile ranges (figure 3). Perhaps unsurprisingly, the highest humidity values tend to coincide with the lowest temperatures. There are comparatively small

differences between the two electricity demand models for these humidity–temperature combinations, i.e. for the 0–25 percentile range except over Florida. For the 25–50 and 50–75 percentile range of temperature, the relative humidity values tend to be lower while the difference in demand projected by the two models is higher. The difference in hourly demand during these temperature quartiles reaches as high as 0.67, 0.66, 0.59 and 0.52 kW over Carolina, Florida, Southeast and Tennessee respectively. This implies that with future warming, humidity will play an important role in amplifying electricity demand even during moderate future temperatures. Further, for the 75–100 percentile range, the difference in the projected demand are also higher for the same relative humidity values, reaching up to 0.5–0.7 kW over the four regions (figure 3). This further reinforces the fact that at high temperatures, even comparatively lower humidity levels can greatly increase human discomfort, thereby increasing the electricity demand.

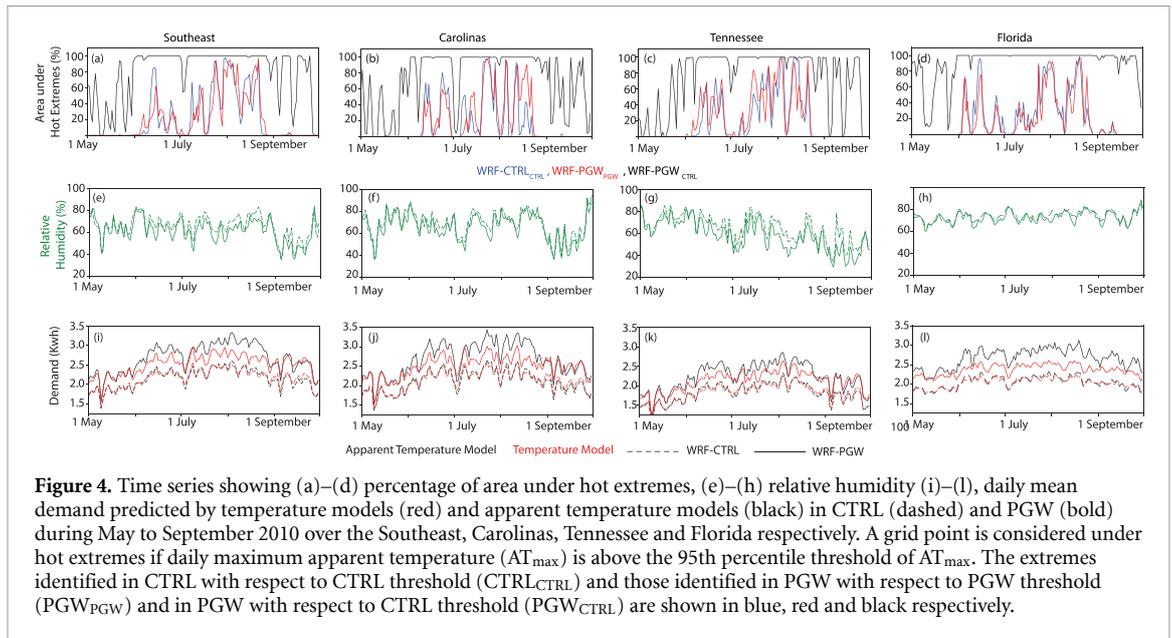


2.3. Role of humidity during extreme hot events

We further illustrate the role of relative humidity during extreme hot events using an example from the summer of 2010 when a majority of the southeastern US was under humid hot extremes (figure 4). We define daily hot extremes for each grid point over the Southeast in CTRL and PGW experiments as exceeding the 95th percentile of the maximum daily apparent temperature (AT_{max}), calculated based on all years (2001–2013) during May–September. We identify hot extremes in CTRL using thresholds based on CTRL ($CTRL_{CTRL}$), whereas we identify hot extremes in PGW using two different thresholds based on: (a) PGW (PGW_{PGW}), and (b) CTRL (PGW_{CTRL}). We then calculate the percentage area under hot extremes for each of the

four regions during May–September (figures 4(a)–(d)). Since these WRF experiments are designed such that historic events reoccur in the future period, the area under $CTRL_{CTRL}$ extremes (shown in blue) and that under PGW_{PGW} extremes (shown in red) show close correspondence, whereas the area under PGW_{CTRL} (shown in black) is significantly larger as it illustrates the influence of the strong mean warming. This absolute increase in hot extremes consequently is the main driver of the future mean increase in demand for both the T and AT model (figures 4(i)–(l)).

During hot extreme events, there occurs a clear amplification of projected demand when AT is considered (figures 4(i)–(l)), despite a slight future decrease in relative humidity (figures 4(e)–(h)). This



amplification is projected to be up to 18%, 21%, 16% and 22% over Southeast, Carolinas, Tennessee, and Florida respectively. This is different from the historical period, where demand is similar for both T and AT. Consistent with figure 3, this signifies the importance of relative humidity in amplifying future demand, especially during the hottest days.

3. Summary and discussion

Humidity can play a crucial role in determining space cooling requirements by causing an increase in human discomfort levels. Although a warming climate leads to an increase in atmospheric moisture content, relative humidity is projected to decrease. However, the combined impact of future relative humidity levels and temperatures on summer electricity demand is not clear. Therefore, we illustrate the importance of incorporating a humidity-based index in the estimation of electricity demand by comparing the results from T- and AT-based models across the southeastern US. The AT-based models are better able to predict electricity demand during the historical period and in a warmer climate, the AT-based models project higher demand across all the regions as compared to the T-based models. These results are consistent with previous studies (Maia-Silva *et al* 2020, Kumar *et al* 2020) that show a higher future demand using humidity-based indices. Further, we highlight the role of relative humidity on electricity demand in a warming climate at high temporal scales. The amplification due to humidity is strongest not only for the hottest but moderate quartiles of the hourly temperature distribution. Given that the amplification of demand happens across the whole range

of temperature distribution, we expect the future demand to be high even outside the peak season for hot extremes. During the hot extremes, despite a slight decrease in relative humidity, higher demand is projected using the AT models. We illustrate this amplifying role of relative humidity on electricity demand for extreme hot events from the summer of 2010.

We acknowledge certain limitations of this work, including uncertainties associated with data and methodology. For instance, while we have confidence in the realism of the simulated change signal given its similarity to other modeling studies, the model used here (WRF) does have mean state biases that can affect the exact number of, e.g. heatwave days (see Liu *et al* 2017, Rastogi *et al* 2020). While we use high temporal scale data, the electricity demand data used in this study is still more spatially aggregated than is ideal for subregional scale planning purposes, highlighting the need to revisit these results at finer spatial scales. Furthermore, we use a 65 °F (18.3 °C) threshold to estimate cooling demand associated with temperature and AT, consistent with previous studies (Rastogi *et al* 2019, Petri and Caldeira 2015). Individuals may require different level of cooling with respect to a particular value of T versus AT. However, AT is calibrated to correspond to the perceived T given current humidity, thus making the two temperatures comparable and descriptive of bulk human perception. This motivates the use of the same threshold for T and AT for the study here. We do not account for technological changes e.g. changes in efficiency of cooling systems that may occur in the future as well as population driven changes in the electricity demand. These factors will influence future demand and in an ideal study, all of these would be known and accounted for in the modeling but given

the well-understood and highly predictive relationship between temperature and demand, we are confident that the current model captures the dominant effects associated with a warming climate. However, in future studies, we plan to extend the framework described here to consider technology adoption and population changes to inform planning studies in electric utilities at subregional scales.

Data availability statement

The data that support the findings of this study are openly available at the following URL/DOI: [10.5065/D6V40SXP](https://doi.org/10.5065/D6V40SXP).

Acknowledgments

We thank Kyoko Ikeda and Dr Changhai Liu from the National Center for Atmospheric Research, for their help with accessing the climate simulation output. The climate simulations output are available at <https://rda.ucar.edu/datasets/ds612.0/>, ERA-5 reanalysis output can be accessed www.ecmwf.int/en/forecasts/datasets/reanalysis-datasets/era5 and electricity demand data is available from US EIA: www.eia.gov/todayinenergy/detail.php?id=43295.

This manuscript has been authored by employees of UT-Battelle, LLC, under contract DEAC05-00OR22725 with the US Department of Energy (DOE). Accordingly, the publisher, by accepting the article for publication, acknowledges that the US government retains a nonexclusive, paid-up, irrevocable, worldwide license to publish or reproduce the published form of this manuscript, or allow others to do so, for US government purposes. DOE will provide public access to these results of federally sponsored research in accordance with the DOE Public Access Plan (www.energy.gov/downloads/doe-public-access-plan). This study is supported by the Grid Modernization Laboratory Consortium, DOE Office of Electricity and Building Technologies Office and the Multiscale Methods for Accurate, Efficient, and Scale-Aware Models of the Earth funded by Advanced Scientific Computing Research program within the U.S. Department of Energy, Office of Science. This research used resources of the Oak Ridge Leadership Computing Facility, which is a DOE Office of Science User Facility supported under Contract DE-AC05-00OR22725. Flavio Lehner is supported by the Regional and Global Model Analysis component of the Earth and Environmental System Modeling Program of the US DOE Office of Biological & Environmental Research via National Science Foundation IA 1947282.

ORCID iDs

Deeksha Rastogi <https://orcid.org/0000-0002-0462-4027>

Flavio Lehner <https://orcid.org/0000-0003-4632-9701>

Teja Kuruganti <https://orcid.org/0000-0003-3704-4026>

Katherine J Evans <https://orcid.org/0000-0001-8174-6450>

Kuldeep Kurte <https://orcid.org/0000-0001-5797-7654>

Jibonananda Sanyal <https://orcid.org/0000-0002-7789-3199>

References

- Auffhammer M, Baylis P and Hausman C H 2017 Climate change is projected to have severe impacts on the frequency and intensity of peak electricity demand across the United States *Proc. Natl Acad. Sci.* **114** 1886–91
- Buzan J R and Huber M 2020 Moist heat stress on a hotter Earth *Annu. Rev. Earth Planet Sci.* **48** 623–55
- Byrne M P and O’Gorman P A 2018 Trends in continental temperature and humidity directly linked to ocean warming *Proc. Natl Acad. Sci.* **115** 4863–8
- Carter L, Terando A J, Dow K, Hiers K, Kunkel K E, Lascurain A R, Marcy D, Osland M J and Schramm P 2018 Climate impacts in the southeast (United States Global Change Research Program) (available at: https://19january2017snapshot.epa.gov/climate-impacts/climate-impacts-southeast_.html)
- Coffel E D, Horton R M, Winter J M and Mankin J S 2019 Nonlinear increases in extreme temperatures paradoxically dampen increases in extreme humid-heat *Environ. Res. Lett.* **14** 084003
- Dee D P et al 2011 The ERA-interim reanalysis: configuration and performance of the data assimilation system *Q. J. R. Meteorol. Soc.* **137** 553–97
- Dutton J A 1976 *The Ceaseless Wind, an Introduction to the Theory of Atmospheric Motion* (New York: McGraw-Hill) pp 273–4
- Fonseca F R, Jaramillo P, Bergés M and Severnini E 2019 Seasonal effects of climate change on intra-day electricity demand patterns *Clim. Change* **154** 435–51
- Hersbach H et al 2020 The ERA5 global reanalysis *Q. J. R. Meteorol. Soc.* **146** 1999–2049
- Kumar R, Rachunok B, Maia-Silva D and Nateghi R 2020 Asymmetrical response of California electricity demand to summer-time temperature variation *Sci. Rep.* **10** 10904
- Liu C H et al 2017 Continental-scale convection-permitting modeling of the current and future climate of North America *Clim. Dyn.* **49** 71–95
- Maia-Silva D, Kumar R and Nateghi R 2020 The critical role of humidity in modeling summer electricity demand across the United States *Nat. Commun.* **11** 1–8
- Massey F J Jr 1951 The Kolmogorov-Smirnov test for goodness of fit *J. Am. Stat. Assoc.* **46** 68–78
- McKinnon K A, Poppick A and Simpson I R 2021 Hot extremes have become drier in the United States Southwest *Nat. Clim. Change* **11** 1–7
- Petri Y and Caldeira K 2015 Impacts of global warming on residential heating and cooling degree-days in the United States *Sci. Rep.* **5** 12427
- Rastogi D, Holladay J S, Evans K J, Preston B L and Ashfaq M 2019 Shift in seasonal climate patterns likely to impact residential energy consumption in the United States *Environ. Res. Lett.* **14** 074006
- Rastogi D, Lehner F and Ashfaq M 2020 Revisiting recent US heat waves in a warmer and more humid climate *Geophys. Res. Lett.* **47** e2019GL086736
- Residential Energy Consumption Survey (RECS) 2009 U.S. Energy Information Administration (available at: <https://www.eia.gov/energyconsumption/>)

- www.eia.gov/consumption/residential/reports/2009/air-conditioning.php)
- Sherwood S C and Huber M 2010 An adaptability limit to climate change due to heat stress *Proc. Natl Acad. Sci.* **107** 9552–5
- Skamarock W C, Klemp J B, Dudhia J, Gill D O, Barker D M, Wang W and Powers J G 2008 A Description Of The Advanced Research WRF version 3 (NCAR Technical note-475+ STR)
- U.S. Energy Information Administration Hourly electricity demand (available at: www.eia.gov/electricity/gridmonitor/dashboard/electric_overview/US48/US48)
- Wang Y and Bielicki J M 2018 Acclimation and the response of hourly electricity loads to meteorological variables *Energy* **142** 473–85
- Weatherly J W and Rosenbaum M A 2017 Future projections of heat and fire-risk indices for the contiguous United States *J. Appl. Meteorol. Climatol.* **56** 863–76