The Goldilocks Zone in Cooling Demand: What can we do better?

Debora Maia-Silva[1], Rohini Kumar[2], and Roshanak Nateghi[3,4,5]

[1]Environmental and Ecological Engineering, Purdue University, West Lafayette, IN, 47906
[2]Department Computational Hydrosystems, Helmholtz Centre for Environmental Research-UFZ, Leipzig, Germany, 04318
[3]School of Industrial Engineering, Purdue University, West Lafayette, IN, 47906
[4]Purdue Climate Change Research Center, Purdue University, West Lafayette, IN, 47906
[5]Center for the Environment, Purdue University, West Lafayette, IN, 47906

Key Points:

- Analysis of historical electricity demand data shows current CDD-based estimates falls short (±25%) of capturing regional comfort zones.
- Extending CDD to include humidity improves characterization of climate-demand nexus under present and future climate conditions.
- Ignoring humidity leaves to significant underestimation of the projected climate-sensitive portion of cooling demand (∼22%).

Corresponding author: Debora Maia-Silva, `dmaiasil@purdue.edu`

Corresponding author: Rohini Kumar, `rohini.kumar@ufz.de`

Corresponding author: Roshanak Nateghi, `rnateghi@purdue.edu`

Abstract

The higher frequency and intensity of sustained heat events have increased demand for cooling energy across the globe. Current estimates of summer-time energy demand are primarily based on Cooling Degree Days (CDD), calculated using a predetermined comfort zone temperature. Through a comprehensive analysis of the observed trends in energy demand across the USA, we show that the current estimates of cooling demand fall significantly short ($\pm$25%) of capturing regional comfort zones. Moreover, given the increasingly compelling evidence that air temperature alone is not sufficient for characterizing human thermal comfort, we extend the widely-used CDD calculation to heat index, which accounts for both air temperature and humidity. Our results demonstrate a significant underestimation of the projected climate-sensitive portion of cooling demand ($\sim$22%) when humidity is ignored. Our findings have significant implications for the security, sustainability, and resilience of the grid under climate change.

Plain Language Summary

Hotter summer days and more frequent and intense heat waves are causing a sharp rise in demand for air conditioning across the globe. Accurate estimation of demand for space cooling is an integral component of resilient planning, operation, and management of the grid. One widely used metric for characterizing this demand is the Cooling Degree Days (CDD), which is calculated based on the difference between the daily temperature mean and a pre-defined base temperature that represents a 'comfort zone'. In this paper, we analyze historical data on climate and energy demand, and find that the most frequently used base temperature of 65°F in CDD calculations leads to mis-characterizing geographically specific 'comfort zones' across the U.S. This can cause significant under- or over-estimations of energy cooling demand. Moreover, we extend the CDD calculations to also account for the role of humidity and demonstrate the cost of ignoring humidity in CDD calculations under present and future climate conditions.

1 Introduction

The thermal comfort of societies is critical not only for human health and well being but also for achieving a high-sustainability future. Despite the direct linkages between cooling demand and each of the 17 Sustainable Development Goals (SDGs), the unprecedented global increase in demand for cooling has been largely absent from today's sustainability debates (Khosla et al., 2020a). Under current socio-economic and climatic conditions, three-quarters of the global population will experience health risk due to exposure to extreme heat events (McGregor et al., 2015), with significant equity and justice implications. The demand for space cooling is expected to witness a threefold increase by 2050 (Birol, 2018); the inability to meet this rising demand sustainably is bound to widen the energy poverty gap and increase GHG (greenhouse gas) emissions, exacerbating climate change and its impacts on modern society.

Air conditioning is touted as an integral component of modern living and a testament to human civilization's progress (Berger, 2004). Moreover, it is an important driver of summer-time peak load—the highest energy demand in a given period—which often sets the key operational and planning parameters in energy infrastructure management (Auffhammer et al., 2017; Jaglom et al., 2014; Reyna & Chester, 2017; van Ruijven et al., 2019; Mukhopadhyay & Nateghi, 2017). With increased intensity and frequency of heat waves and accelerated adoption of air conditioning, access to accurate estimates of cooling demand (during both peak and off-peak hours) has become an important pillar in energy systems planning (Coumou & Rahmstorf, 2012; Mukherjee & Nateghi, 2017a, 2017b; IEA, 2008). Accurate characterization of summer-time peak load is particularly important for residential customers, which represent the most climate-sensitive segment of the energy sector (Obringer et al., 2019; Khosla et al., 2020b; Obringer, Mukherjee, & Nateghi, 2020; Isaac & van Vuuren, 2009; Sailor, 2001).

Cooling Degree Day (CDD) is a practical and widely used measure for quantifying summer-time space cooling demand in energy planning (Day, 2006; Biardeau et al., 2020). CDD represents the number of degrees a day's average temperature exceeds a prespecified set-point temperature, and any value that exceeds this base temperature is assumed to trigger demand for cooling. CDD's set-point temperature represents a comfort zone—aka a 'Goldilocks zone' for human thermal comfort, where it is neither too cold nor too hot. The selected comfort zone temperature is often arbitrarily set at 65°F (18.3°C) in global and regional energy planning studies (Biardeau et al., 2020; Waite et al., 2017; Sivak, 2009; Petri & Caldeira, 2015a; Goldstein et al., 2020; Davis & Gertler, 2015; Khan et al., 2021). More specifically, while in certain applications such as building-level thermal comfort studies (Shin & Do, 2016) empirically derived base temperatures have been used, in studies related to energy infrastructure planning—the focus of this paper—CDD's set point temperature is almost always set at 65°F (18.3°C) (Biardeau et al., 2020; Waite et al., 2017; Sivak, 2009; Goldstein et al., 2020; Davis & Gertler, 2015).

There are two fundamental caveats to the approaches that calculate CDD based on the generic set-point value of 65°F for sustainability and resilience analytics in energy infrastructure planning and management. Firstly, the set-point value of 65°F was derived decades ago, with no consideration of climate change and thus might no longer be a representative value under present and future climate conditions. Secondly, previous studies have shown that air temperature is a necessary but not sufficient measure of heat stress (Buzan et al., 2015; Maia-Silva et al., 2020; Li et al., 2020; Raymond et al., 2020). However, CDD does not take humidity into account (Day, 2006), rendering its effectiveness in capturing human thermal comfort questionable. In the light of the recent record-breaking blackouts last summer (Borunda, 2020) along with increased frequency and intensity of heatwaves (Hulley et al., 2020), the energy sector must address these shortcomings to mitigate the growing threats of climate change and enhance the security, sustainability, and resilience of the grid. Otherwise, incomplete and inaccurate understandings of how human thermal comfort relates to cooling demand will hamper urgent transformations needed to unlock sustainable pathways, and will likely increase the risk of path-dependent trajectories in the energy sector.

We address these fundamental gaps by deriving geographically specific CDDs and extending the calculation of CDD to also account for humidity. Specifically, we first derive geographically specific CDDs for each state[1], using summer-time (May to September) residential energy consumption data (1990-2016) to establish region-specific optimal set-point temperatures. By comparing these values with CDDs based on 65°F set-point temperature, we assess the divergence in values throughout the American territory. We discuss the implications of the over- or underestimation of the newly calculated CDDs for energy planning under both present and future climate conditions.

Additionally, to account for the critical role of humidity, we go beyond air temperature in calculating CDD. In particular, we extend the CDD method to heat index—a widely used climate measure for human heat comfort that includes humidity (Buzan et al., 2015; Anderson G. Brooke et al., 2013; Willett & Sherwood, 2012; Maia-Silva et al., 2020)—and harness CMIP5-GCM climate scenarios to make projections under climate change. Our results demonstrate a considerable deviation of the optimal set-point temperatures from the base temperature of 65°F (18.3°C) in most states, with an average deviation of 10%. In addition, the projected heat index-based CDDs show a considerable increase in value as compared to air temperature, with an average of 22% higher

[1] While state boundaries do not always coincide with climate boundaries, our state-level analysis is motivated by providing insights that are relevant to state-level policymakers and energy planners.

values. Our findings reveal that a unilateral focus on air temperature-based CDDs with a generic set-point temperature in energy systems planning undermines the resilience of the grid under climate change, especially during extreme heat events.

The structure of the paper is as follows. Details of the data collection, data processing, and methodology are summarized in Section 2. Results are presented in Section 3. The paper concludes by summarizing findings and discussing the significance of results in Section 4.

2 Data and Methods

2.1 Observed Climate Data

The observed climate data is acquired at a sub-daily (3 hourly) time scale for the period of 1990-2016 from the NCEP North American Regional Reanalysis (NARR) at a 32 kilometer spacial resolution (Mesinger et al., 2006; NCEP, 2019; CIESIN, 2019). Data is aggregated at a monthly level to match the chronological scale of electricity consumption data and weighted by population density when aggregating to the state level. Specifically, the 2010 UN-adjusted Gridded Population of the World dataset (Version 4) is used for this work, collected from the Socioeconomic Data and Applications Center (SEDAC; http://sedac.ciesin.columbia.edu). This procedure to give higher weight where population is concentrated when averaging state level data is in line with previous studies in residential electricity demand (Schlenker & Roberts, 2009; Kumar et al., 2020).

2.2 Projected Climate Data

While analyzing observational data is essential for understanding past variability in historical events, they provide limited knowledge for anticipating the future, especially under non-stationary conditions. Using projected climate data is essential for characterizing the growing effects of climate variability and change on the energy sector (Maia-Silva et al., 2020; Auffhammer et al., 2017; Obringer, Kumar, & Nateghi, 2020). To extend our analysis into the future such that our findings are relevant for energy planning, projected climate data are acquired for the period of 2031–2050. This timeline is chosen due to the fact that the year 2050 is consistently used as a target year for mid-term planning in energy reports (EIA, 2020a; IPCC, 2014). This timeline is practical as it allows for considering climate change effects on the sector without having to consider significant transformations to the architecture of the electric grid.

The projected climate data used in this paper are derived from five different Global Circulation Models (GCM), namely, Geophysical Fluid Dynamics Laboratory Earth Systems Model (GFDL-ESM2M), Hadley Global Environment Model 2 - Earth System (HadGEM2-ES), IPSL Earth System Model for the 5th IPCC report (IPSL-CM5A-LR) (IPCC, 2014), Atmospheric Chemistry Coupled version of MIROC-ESM, a Earth System model (MIROC-ESM-CHEM), and the Norwegian Earth System Model (NorESM1-M). The data are considered under the emission scenario that has an end-of-century radiative forcing equal to 8.5 Wm^{-2}—Representative Concentration Pathway that is characterized by high greenhouse emission levels, RCP8.5, (Warszawski, 2014; Nateghi & Mukherjee, 2017). For the state level averaging, data is approximated by a 0.5 degree spatial resolution ($\sim$ 50 km) (Hempel, 2013) and weighted by population.

2.3 Electricity Data

Similar to the temporal resolution of the observed climate data, monthly electricity data sales data are used in this work. Data are acquired from the U.S. Energy Information Administration (EIA, 2020c) over the years of 1990–2016 at a state level for the residential sector. To isolate the climate effects from the electricity data—which are influenced by various factors such as technological changes, policy implementation, demographic shifts, etc. (van Ruijven et al., 2019; Mukherjee et al., 2018; Auffhammer et al., 2017)—we de-trended the raw, state-level electricity data. We leveraged a well-established de-trending method for isolating the climate effects (Sailor & Muñoz, 1997), which is widely-used in the energy research literature (Khoshbakht et al., 2018; Santágata et al., 2017; Parkinson & Djilali, 2015; Brown et al., 2016; Alipour et al., 2019; Mukherjee & Nateghi, 2017a). Electricity demand data are initially normalized by the state-level population to obtain a per capita value of consumption. The de-trending process involves the following steps:

$$E(y) = \frac{\sum_{y=1}^{n_{years}} \sum_{m=1}^{12} E(m,y)}{n_{years}} \tag{1}$$

Where the total years, n_{years}, range from 1990–2016; m denotes the month and y denotes the year.

An adjustment factor is calculated per year, and it is the sum of the monthly per capita demand divided by the yearly consumption $E(y)$.

$$F_{adj} = E(y)^{-1} \sum_{m=1}^{12} E(m,y) \tag{2}$$

The final de-trended demand is obtained by dividing the monthly consumption by the previous calculated adjustment factor.

$$E(m,y)_{adj} = E(m,y)/F_{adj} \tag{3}$$

2.4 CDD Calculation

Once climate and electricity data are aggregated and available, the next step is CDD calculation. Daily CDD is calculated as shown below in Equation 4.

$$CDD_{daily} = \begin{cases} 0, & T_d < T_b \\ T_d - T_b, & T_d > T_b \end{cases} \tag{4}$$

Where T_d represents daily average temperature and T_b represents the base temperature/set-point temperature selected for the CDD calculation. CDD is usually aggregated to annual or monthly levels by summing the respective daily values.

While T_b is often arbitrarily set to 65°F (18.3°C) (Biardeau et al., 2020; Goldstein et al., 2020), we leveraged the well-established energy signature method (F. R. Jacobsen, 1985; Brown et al., 2014; Bhatnagar et al., 2018; Lee et al., 2013; Sailor & Muñoz, 1997) to derive geographically specific CDD set-points for all 48 CONUS states. The analysis is done by examining scatter plots of energy consumption versus climate variables to select a vertex that reflect cooling sensitivity, as characterized by a sharp increase in demand at a certain climate threshold value. The energy signature method is performed in three steps:

1. Iteratively process the data to select relevant intervals, conducive to identifying the sensitivity points (or base values/set-points);
2. Fit piece-wise constant regression models to each region.
3. Repeat steps 1 and 2 until distinct vertex points are detected.

Considering the uncertainty associated with this method, confidence intervals with 10,000 bootstrap repetitions are calculated for each base value. At the end of the process, the 48 CONUS states have CDD base values for air temperature and heat index. An example of the energy signature method is illustrated in Figure 1.

The geographically-specific CDD based values are then compared against the widely-used 65°F (18.3°C) value. The deviations are spatially illustrated in Section 3. Reduced form equations are then used to characterize the implication of the discrepancies between the derived and widely-used set point temperature of 65°F (18.3°C) in-terms of energy demand.

3 Extending the CDD Calculation to Include Humidity

To extend the CDD analysis under climate change to also account for humidity humidity, heat index-CDD was calculated using the Energy Signature method discussed previously for the 2031-2050 time period, as illustrated in Figure 1(b) and 1(d). Heat index (HI), also called apparent temperature, describes what the temperature feels like to the human body when relative humidity is combined with air temperature (Buzan et al., 2015; Rothfusz, 1990). Characterizing the climate-sensitivity of energy demand requires accounting for the synergistic effects of surface temperature and humidity on human body and; accounting for the role of humidity, therefore, is necessary for modeling demand. Heat index is calculated following the equation bellow:

$$\begin{aligned} HI = -42.379 + 2.04901523\, T_F + 10.14333127\, RH - 0.22475541\, T_F RH \\ -6.83783x10^{-3} T_F^2 - 5.481717x10^{-2}\, RH^2 + 1.22874x10^{-3} T_F^2\, RH \\ +8.5282x10^{-4} T_F\, RH^2 - 1.99x10^{-6} T_F^2\, RH \end{aligned} \tag{5}$$

Where (T_F) denotes the air temperature, RH denotes relative humidity and HI are measured in degrees Fahrenheit.

4 Characterizing Air Conditioning Prevalence and Affordability

CDD analysis has other applications beyond the direct use of the CDD index. CDD is used as an input to different measures of climate comfort, such as cooling penetration (PNT), and to calculate the ratio of households that could afford air conditioning (Smax). We extended our detailed CDD analysis to these two other indexes due to their use related to human heat comfort (S. Laine et al., 2019; Jakubcionis & Carlsson, 2017). PNT is calculated as the following equation (S. Laine et al., 2019). It represents the percentage of homes in a certain area that have air conditioning.

$$PNT = \begin{cases} 26.33\ \ln CDD - 81.69, & 0 < CDD < 920 \\ 97.3, & CDD > 920 \end{cases} \tag{6}$$

CDD is the summation of annual CDD.

Smax represents the fraction of households in a certain area that would acquire AC if they could afford it (Jakubcionis & Carlsson, 2017) and is calculated as shown below.

$$S_{max} = 1 - 0.949 e^{-0.00187 CDD} \tag{7}$$

CDD here denotes the summation of annual CDD.

5 Results

This section starts by first summarizing the results associated with deriving geographically specific CDDs. It is then followed by extending the CDD calculation to also account for humidity, discussing the associated implications under present and future climate conditions.

5.1 CDD Base Value Heterogeneity Across the CONUS

To test the hypothesis of whether 65°F (18.3°C) adequately captures thermal comfort across the CONUS, we leverage the energy signature method (Lee et al., 2013; Bhatnagar et al., 2018; F. Jacobsen, 1985; Zmeureanu & Renaud, 2008) discussed in the previous section. Implementing the energy signature method involved using the average monthly residential energy consumption data from 1990 to 2016 (EIA, 2020b) together with air temperature data for the same period (NARR, 2020). The differences between the 65°F (18.3°C) and derived optimal set-points are depicted in Figure 2(a), with states shaded in orange (blue) representing CDDs with higher (lower) than 65°F (18.3°C) set-point temperatures. Figure 3(a) illustrates this same variation as a scatter plot of CDDs with fixed and regionally varying threshold points, such that states farther from the reference (1:1) line show a greater deviation of the geographically specific set-point temperature from the 65°F (18.3°C). The state of Washington is excluded from Figure 2 owing to the relative climate insensitivity of its summer-time demand during the study's time span (Petri & Caldeira, 2015b; Hamlet et al., 2010; Maia-Silva et al., 2020)(also see Supplementary Figure 1).

There are significant deviations of the derived base temperature from 65°F (18.3°C), with 30% of the CONUS states showing absolute variation higher than 10% (6.5°F). In Southern states, the optimal set-point temperature is significantly higher than the conventional 65°F base value. For instance, Texas (TX) and Florida (FL) show notable deviations from 65°F, with significant implications for the states' energy planning, given their high population and energy consumption, especially during hot summers. To quantify the implications of these deviations from the commonly used set-point temperature for cooling demand, we harness state-specific reduced form equations established via regressing summer-time energy demand on CDD.

Figure 2(b) depicts the implication of the derived CDD variable set-point temperature for the climate-sensitive portion of cooling demand—reported in-terms of the percentage shift in state-level energy consumption, with variations up to 40%. This result demonstrates that in states with negative variations (shaded in gray) the conventional set-point temperature overestimates the climate-sensitive portion of the energy demand. The overestimation has a higher absolute variation, as seen in states like Colorado (CO, -32.8%) and Maine (ME, -38.1%). Conversely, in states with positive variations (shaded in red) the conventional (fixed point) approach underestimates the climate-sensitive demand. While these underestimations are lower in absolute value, they have significant implications in key energy-intensive southern states such as Florida (FL, 9%) and Georgia (GA, 8.9%). Figure 3(b) further illustrates this point for the nine states: Florida (FL), Georgia (GA), Louisiana (LA), Kentucky (KY), North Dakota (ND), Montana (MT), Maine (ME), New Hampshire (NH) and Oregon (OR), showing the values for over- (bars in blue) and under-estimations of energy demand (bars in orange). Here the values refer to the differences in per capita energy estimates in MWh—estimated based on the relative differences in consumption shown in Fig. 2(b) and considering the respective state populations (Bureau, 2020). Notably the large differences between the fixed and updated baseline methods can be observed for the states of Florida (underestimation by more than 800 K MWh) and Oregon (overestimation by 500 K MWh).

The states where the conventional approach leads to an underestimation of cooling demand present serious challenges to energy planning. More specifically, even a small deviation from forecasted and/or anticipated demand in these states can prove costly not only to energy infrastructure planners and operators but also the consumers. For example, a 9% variation in Florida—in terms of its June 2016 demand—is equivalent of maintaining 55,000 Floridian households' energy for an entire year. In a state where air conditioning takes almost a third of the summer-time energy consumption, this is a serious cause for concern in energy planning (EIA, 2020c).

Besides the significant implications of access to geographically specific CDDs for demand forecasting, it has serious consequences for other key elements in energy planning, namely, estimating air conditioning adoption rates, since CDD is the base for other indexes calculations. For example, the use of generic CDDs in calculating Cooling Penetration (PNT) (S. Laine et al., 2019) and the fraction of households that would acquire AC if they could afford it (S_{max}) (Jakubcionis & Carlsson, 2017) would yield misestimations as high as 9% and 17%, respectively, as we can see in Figure 4 for observed values between 1990 and 2016. PNT is also significantly affected for projected CDD and humidity-based CDD, as seen in Supplementary Figure S2 and S3 (up to 28% change for air CDD and a max of 7% in heat index CDD—total average of 5% and 2%, respectively). S_{max} has a greater variation for projected data, shown in Supplementary Figures S4 and S5, with an average of 9% change for air temperature CDD and 6% for heat-index based CDD estimates. Compared to the PNT estimates, S_{max} has a higher variation partly due to nature of its estimation procedure that do not include any threshold limits (Equation 7). Nevertheless both variables (PNT and S_{max}) show the overwhelming underestimation in the projected CDD estimates (states in blue; Fig. 4, see also Supplementary Fig. S4 and S5), which, as presented, are a source of great concern in energy planning.

5.2 On the Role of Humidity

Considering the significant challenges posed by climate change, not only in terms of increased frequency and intensity of extreme heat events over time (IPCC, 2014; Auffhammer et al., 2017; Mehrabi et al., 2019; Creutzig et al., 2018), but also the growing importance of humidity in shaping future air conditioning demand (Maia-Silva et al., 2020; Bhatnagar et al., 2018; Biardeau et al., 2020), we analyze the projected changes in CDDs based on air temperature and contrast them with a similar measure based on heat index, which accounts for both air temperature and humidity. We harness the climate projection data-set of five CMIP5-GCMs under the RCP8.5 for the period of 2031-2050.

Heat index-based CDDs are calculated using the same signature method that is used for calculating air temperature-based CDDs. In other words, we estimate the geographically varying optimal heat-index values based on electricity consumption data. For conducting projections under climate change, we use the 2031-2050 time period to be consistent with the time-span most commonly used in mid-term energy planning reports (EIA, 2020a; IPCC, 2014), while still accounting for climate change effects.

Figures 5(a) and 5(b) demonstrate how heat index-based CDD compares with air temperature-based CDD for the geographically-specific (updated CDD) and the conventional 65°F (18.3°C) set-point values, respectively. There is a greater variation across states when using the conventional set-point temperature, suggesting that ignoring humidity in CDD calculations will likely lead to underestimating human heat comfort – varying between ∼22% and ∼36% variations as depicted in Figure 5(a) and Figure 5(b). States with high energy consumption such as Texas (TX, 20.9%) and Florida (FL, 70.5%), present significant underestimation of CDD projection when compared with the geographically-specific CDD. Throughout the CONUS, the variation is overwhelmingly positive (shades of orange) – a clear sign of underestimation in projected energy demand when comparing the conventional air-based CDD approach with the heat index based estimates.

Figure 5(c) and 5(d) illustrate the same information, but in the form of scatter-plots, with an average of 22% of projected (2031-2050) underestimation comparing the updated CDD, including top energy-consuming states like California (CA) and Florida (FL). It is clear that most states are shaded in blue – higher values for the heat index CDD – showing once more the significant potential for underestimation when only focusing on air temperature CDDs, either the updated values or the convention fixed set-point values. The same analysis was conducted for observed data (1990-2016), shown in Supplementary Figure S6, that even though the underestimation (states in blue) are not as acute as when considering the future effects of climate change (Fig. 5(c) and Fig. 5(d)), still 56% of the states present underestimation. Overall these results emphasise the importance of accounting for the humidity related heat-stress measures in estimation of CDD and climate-sensitive portion of energy demand projections.

6 Discussion and Concluding Remarks

Increased demand for cooling has been identified as a critical blind spot in today's sustainability discourse (Khosla et al., 2020a). Inadequate characterization of human thermal comfort poses significant challenges to the security and resilience of the grid and present obstacles to achieving SDGs (Biardeau et al., 2020; Li et al., 2020; Isaac & van Vuuren, 2009). Despite its widespread use in characterizing thermal comfort, CDD is not a universally reliable proxy for cooling energy demand.

Here, we examine the consequences of calculating CDD based on a generic set-point temperature of 65°F (18.3°C) in energy infrastructure planning. Specifically, we use observed trends in summer-time energy demand to derive geographically specific comfort-zone temperatures across CONUS, and demonstrate the degree to which generic CDDs over- or underestimate demand for cooling by disregarding geographical heterogeneity in thermal comfort across the country. Moreover, by extending the calculation of CDD to also account for humidity, we demonstrate the degree to which current approaches fall short in capturing human thermal comfort under present and future climate conditions.

As the world gets hotter and the demand for cooling energy soars, utilities face unprecedented challenges in reliably balancing the grid, especially during the more frequent and prolonged heat events (Auffhammer et al., 2017; Coumou & Rahmstorf, 2012; Davis & Gertler, 2015; Maia-Silva et al., 2020). We demonstrate that relying on conventional CDD for energy projections and ignoring the critical role of humidity will be costly for both utilities and customers. Credible projections of demand, both in the near term and future, allow policymakers and utilities to develop more sustainable and proactive plans. For instance, policy levers such as carbon tax and demand-side management can decelerate the adoption of AC units, increase the share of renewable generation and incentivize investments in energy-efficient appliances. Additionally, passive cooling designs and nature-inspired construction methods can lower the temperature in buildings and mitigate the soaring demand for cooling. Such design solutions include the use of shades, enhanced wind circulation, green rooftops, evaporative cooling, glass modifications, and bio-inspired cooling technologies (Fu et al., 2020; De Angelis et al., 2017; Nie et al., 2020). Higher vegetation in the urban environment has also been shown to have a modulating effect during extreme heat events (Bounoua et al., 2015; Susca et al., 2011; Melaas et al., 2016).

In summary, our study underscores the value of leveraging the observed trends in energy demand in deriving optimal, regionally-specific comfort zone levels for calculating CDDs. Moreover, we demonstrate that disregarding humidity leads to underestimating demand under climate change, with considerable implications for the security of the grid. These insights contribute to pushing the sustainable development agenda and efforts in delivering sustainable cooling to society.

7 Open Research

Datasets used in this study are freely available from referenced sources: U.S. Energy Information Administration (EIA, 2020b, 2020c), NCEP North American Regional Reanalysis (NARR) (Mesinger et al., 2006; NCEP, 2019; CIESIN, 2019), and CMIP5 model outputs through the Earth System Grid Federation (ESGF) gateways.

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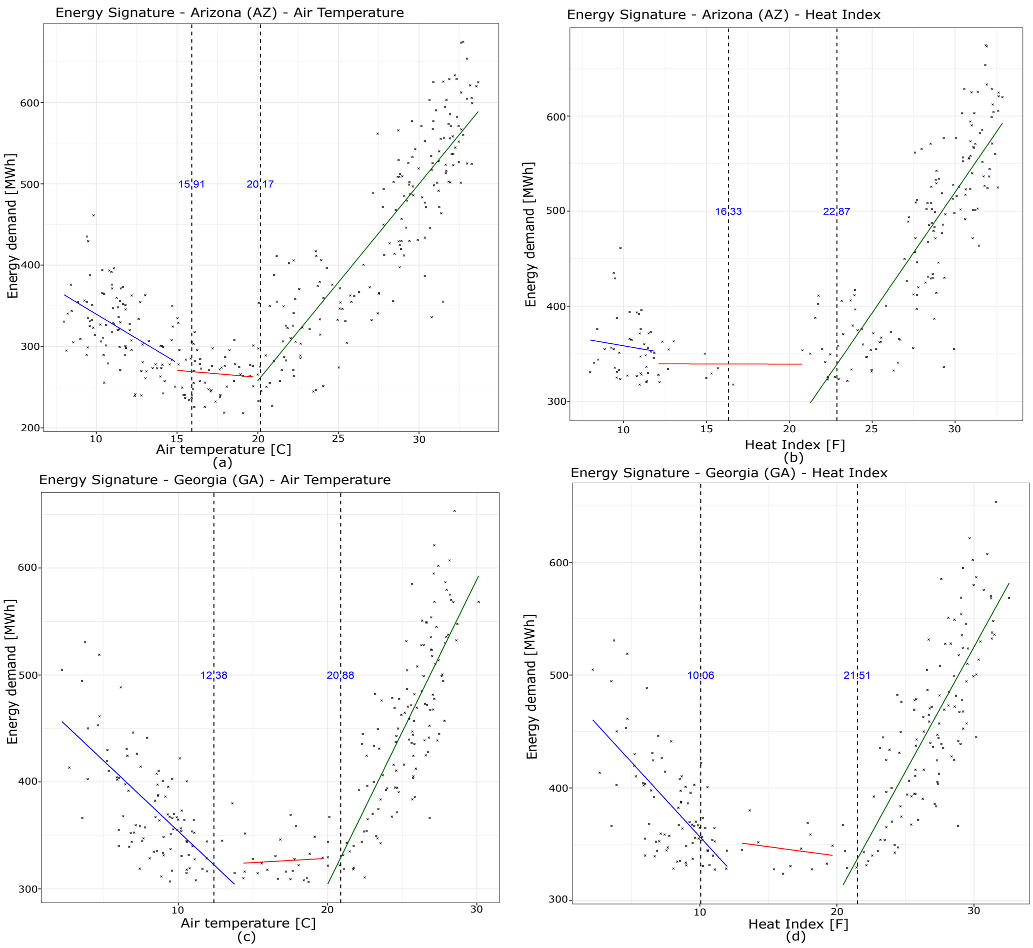

Figure 1. An example of the Energy Signature Method conducted for the state of Arizona (AZ) for air temperature CDD (a) and heat index CDD (b); for the state of Georgia (GA) for air temperature CDD (c) and heat index CDD (d). In blue, the determined heating and cooling set points for each state and variable. The three regression lines are identified in the figures, and the base points are the intersection of said lines.

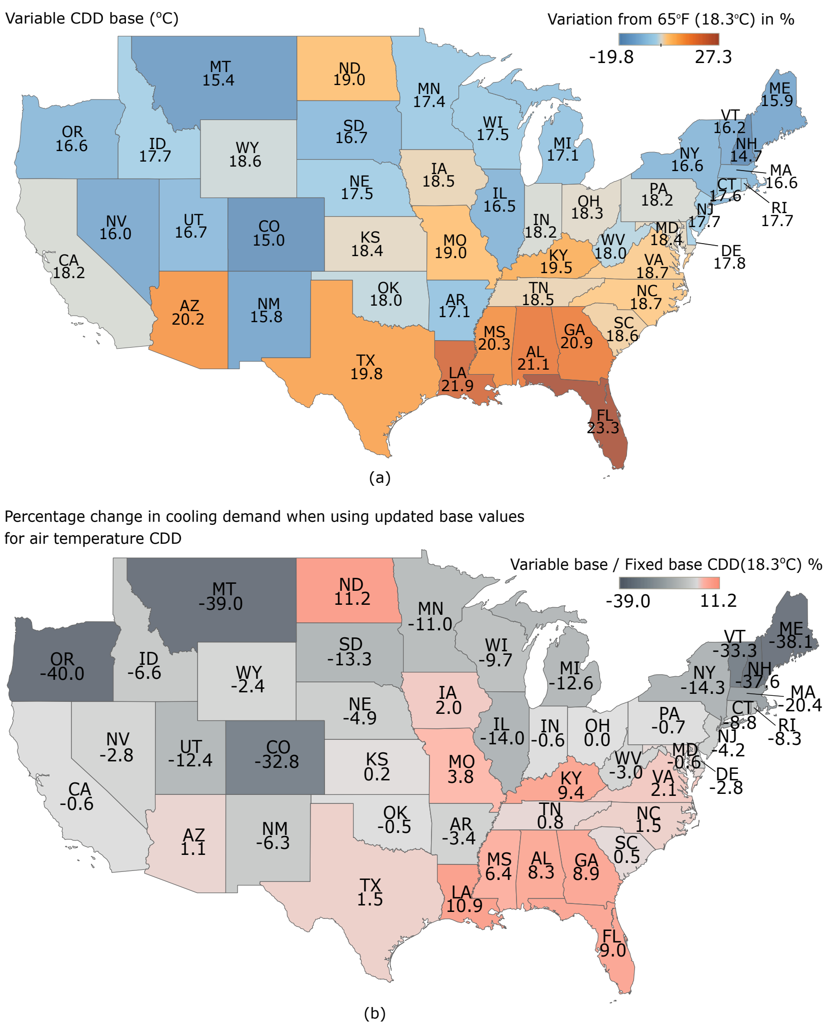

Figure 2. (a) The derived CDD air temperature set-points for the CONUS states. In orange (blue), the darker the state color, the greater its positive (negative) variation from the traditionally used 65°F (18.3°C) set-point.(b) Percentage change in the climate-sensitive portion of residential cooling demand in all 48 CONUS states when using the updated set-point for air temperature CDD.

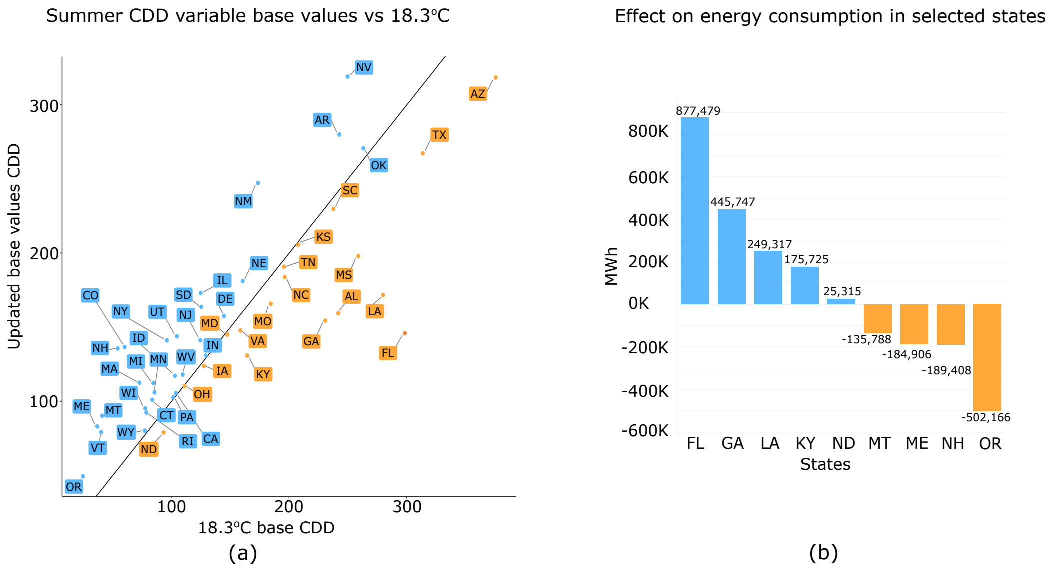

Figure 3. (a) Comparison of the variable set-points (y-axis) with the fixed 65°F (18.3°C) set-point (x-axis). (b) The resulting impact on energy consumption in thousands of MWh for the states of Florida (FL), Georgia (GA), Louisiana (LA), Kentucky (KY), North Dakota (ND), Montana (MT), New Hampshire (NH) and Oregon (OR).

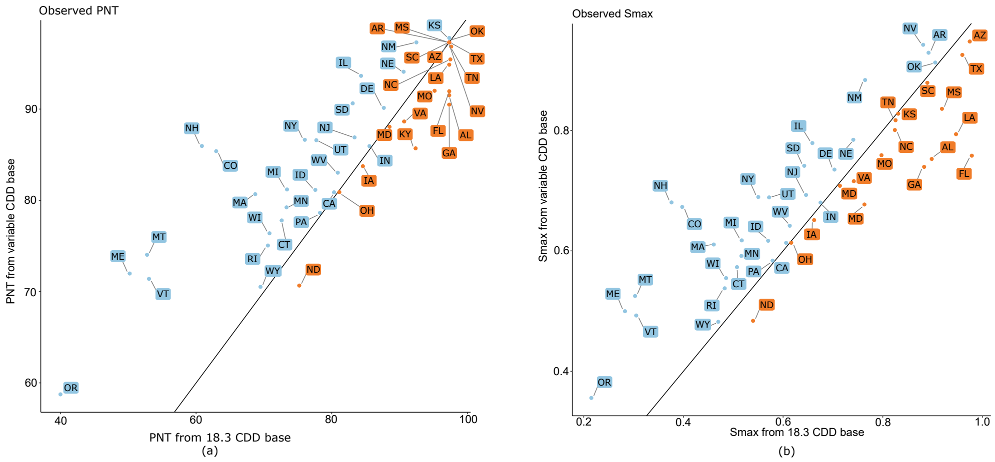

Figure 4. (a) Percentage variation in PNT average (1990-2016) for the 65°F (18.3°C) air temperature set-point and the updated/variable set-point values. (b) Similar to (a), but for Smax values. (1:1) line for reference.

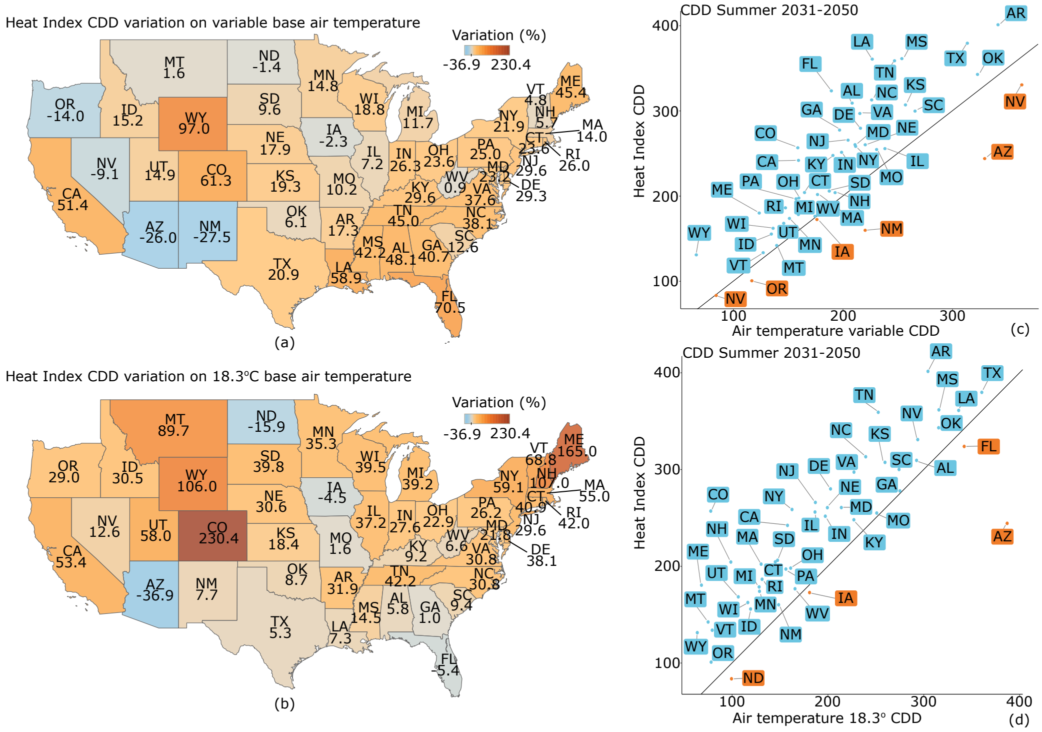

Figure 5. (a) Percentage variation in CDD average (2031-2050) between heat index and the updated set-points for air temperature. (b) Similar as (a), but for the 65°F (18.3°C) air temperature set-point. (c) Comparison of heat index summer CDD (2031-2050) and the updated set-points for air temperature. (1:1) line for reference. States in blue have a higher value for heat index CDD; states in orange, lower, when compared to the updated set-points for air temperature. (d) Similar as (c), but for the 65°F (18.3°C) air temperature set-point.