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Key Points:

- Analysis of electricity demand shows that the widely used Cooling Degree Days (CDD) estimates fall short of capturing regional thermal comfort zones
- Estimates of air conditioning penetration and affordability based on traditional calculation of CDD can lead to significant misestimation
- Extending CDD calculations to include humidity improves the characterization of climate-demand nexus under present and future climate

Supporting Information:

Supporting Information may be found in the online version of this article.

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The Goldilocks Zone in Cooling Demand: What Can We Do Better?

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Abstract The higher frequency and intensity of sustained heat events have increased the demand for cooling energy across the globe. Current estimates of summer-time energy demand are primarily based on Cooling Degree Days (CDD), representing the number of degrees a day's average temperature exceeds a predetermined comfort zone temperature. Through a comprehensive analysis of the historical energy demand data across the USA, we show that the commonly used CDD estimates fall significantly short (±25%) of capturing regional thermal comfort levels. 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 indicate significant mis-estimation of regional thermal comfort 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 heatwaves 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 by measuring the difference between the mean daily temperature and a pre-defined base temperature that represents a "comfort zone." In this study, 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 comfort zones across different geographic areas in the United States. This can cause significant under- or over-estimations of cooling energy demand. Moreover, we extend the temperature-based 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

Maintaining 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., 2020). 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; Mukhopadhyay & Nateghi, 2017; Reyna & Chester, 2017; van Ruijven et al., 2019). 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; IEA, 2008; Mukherjee & Nateghi, 2017a, 2017b). Accurate characterization of summer-time peak load is particularly important for residential customers, which represent the most climate-sensitive segment of the energy sector (Isaac & van Vuuren, 2009; Khosla et al., 2020; Obringer et al., 2019; Obringer, Mukherjee, & Nateghi, 2020; Sailor, 2001).

Cooling Degree Day (CDD) is a practical and widely used measure for quantifying summer-time space cooling demand in energy planning (Biardeau et al., 2020; Day, 2006; Deroubaix et al., 2021; Lebassi et al., 2010). CDD represents the number of degrees a day's average temperature exceeds a pre-specified 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; Davis & Gertler, 2015; Goldstein et al., 2020; Khan et al., 2021; Petri & Caldeira, 2015; Sivak, 2009; Waite et al., 2017). 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—which is the focus of this study—CDD's set-point temperature is almost always set at 65°F (18.3°C; Biardeau et al., 2020; Davis & Gertler, 2015; Goldstein et al., 2020; Sivak, 2009; Waite et al., 2017).

The use of CDD for studying the climate-energy nexus has limitations since the CDD calculation is solely based on air temperature, and that the metric was originally derived to study buildings' thermal comfort. Additionally, 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. First, 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. Second, previous studies have shown that air temperature is a necessary but not sufficient measure of heat stress (Angeles et al., 2018; Buzan et al., 2015; Li et al., 2020; Maia-Silva et al., 2020; Ortiz et al., 2018; Pokhrel et al., 2018; Raymond et al., 2020). However, temperature-based CDD calculations do not take humidity into account (Day, 2006). This renders the effectiveness of CDD as a metric for capturing human thermal comfort questionable. In the light of the recent record-breaking blackouts last summer (Borunda, 2020) along with the 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 first 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 of the conterminous United States (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), using summer-time (May to September) residential energy consumption data (1990–2016) to establish region-specific optimal set-point temperatures. We then measure the deviations between these values and the CDD estimates based on 65°F set-point temperature throughout the CONUS territory. We discuss the implications of the over- or underestimations, as revealed by 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 (HI)—a widely used climate measure for human heat comfort that includes humidity (Brooke et al., 2013; Buzan et al., 2015; Maia-Silva et al., 2020; Willett & Sherwood, 2012)—and harness CMIP5-GCM climate scenarios to make projections under climate change.

We provide the details of the data collection, data processing, and methodology in Section 2. We then give a detailed account of our results in Section 3. Finally, we summarize our findings and discuss the significance of our results in Section 4. 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%. Our findings reveal that a singular 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.

2. Data and Methods

2.1. Observed Climate Data

We acquired the observed climate data 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 km spatial resolution (CIESIN, 2019; Mesinger et al., 2006; NCEP, 2019). We aggregated the data to a monthly level to match the chronological scale of electricity consumption data, and weighted the data by population density when aggregating to the state level. Specifically, the 2010 UN-adjusted Grid Population of the World data set (Version 4) is used for this work, collected from the Socioeconomic Data and Applications Center (SEDAC; http://sedac.ciesin.columbia.edu). Giving higher weights to regions with higher population densities when averaging state level data is in line with previous studies on residential electricity demand (Kumar et al., 2020; Schlenker & Roberts, 2009).

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 the projected climate data is essential for characterizing the growing effects of climate variability and change on the energy sector (Auffhammer et al., 2017; Maia-Silva et al., 2020; Obringer, Kumar, & Nateghi, 2020). To extend our analysis into the future such that our findings are relevant for medium and long-term energy planning, the projected climate data were acquired for both future period of 2031–2050 and also the historical period of 1990–2016. The 2031–2050 timeline is chosen due to the fact that the year 2050 is consistently used as a target year in energy planning 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 electrical grid.

The projected climate data used in this study 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 fifth 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 climate model projection data-sets used in our analysis are obtained from the Inter-Sectoral Impact Model Intercomparison Project (ISI-MIP [Warszawski et al., 2014]); and are part of the CMIP5 database (Taylor et al., 2012). These climate model datasets are bias-corrected using a trend-preserving approach (Hempel et al., 2013); and have been widely used in several impact assessment studies (see www.isimip.org for details). Here, we considered the climate projection estimates under the Representative Concentration Pathway (RCP) 8.5 emission scenario that has an end-of-century radiative forcing equal to 8.5 Wm^{-2}; and is characterized by a highest greenhouse emission level (Nateghi & Mukherjee, 2017; Taylor et al., 2012; Warszawski et al., 2014). Finally, we aggregated these bias-corrected climate projection data to obtain the state-level estimates taking into account the state boundary and corresponding population estimates as a weighing factor, which is in-line with previous studies (Biardeau et al., 2020; Kumar et al., 2020).

2.3. Observed Electricity Demand Data

Similar to the temporal resolution of the observed climate data, we used monthly electricity sales data in this work. We collected the data from the U.S. Energy Information Administration (EIA, 2020c) over the years of 1990–2016 at a state level for the residential sector. We then normalized the electricity demand data by the state-level population to obtain a per capita value of consumption.

To isolate the climate effects from the electricity data, which are influenced by various factors such as technological changes, policy implementation, and demographic shifts (Auffhammer et al., 2017; Mukherjee et al., 2018; van Ruijven et al., 2019), we de-trended the raw, state-level electricity consumption data. There are different de-trending approaches proposed in the literature (Bessec & Fouquau, 2008). The method used in this study (Sailor & Muñoz, 1997) is one the most widely used approaches in the climate-energy research literature and its effectiveness has been extensively documented (Alipour et al., 2019; Brown et al., 2016; Khoshbakht et al., 2018; Mukherjee & Nateghi, 2017a; Parkinson & Djilali, 2015; Santágata et al., 2017). 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 by summing the monthly per capita demand and dividing it by the yearly average consumption $E(y)$.

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

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

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

2.4. CDD Calculation

Once the climate and electricity data are aggregated at a state level, the CDD for a given day can be calculated as (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. The daily CDD is usually aggregated to annual, seasonal, or monthly levels by summing over the respective daily values.

While T_b is often arbitrarily set at 65°F (18.3°C; Biardeau et al., 2020; Goldstein et al., 2020), we leveraged the well-established Energy Signature method (Bhatnagar et al., 2018; Brown et al., 2014; Jacobsen, 1985; Lee et al., 2013; Sailor & Muñoz, 1997) to derive geographically specific CDD set-points for all 48 Lower 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. More specifically, the Energy Signature method is performed in the following three steps:

1. Iteratively process the data to select relevant intervals that are 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 re-samples are calculated for each base value. At the end of the process, the CDD base values for both air temperature and heat index are identified for each of the 48 CONUS states. An example of the Energy Signature method is illustrated in Figure 1.

We compared the derived geographically specific CDD base values with the widely used 65°F (18.3°C). The deviations are spatially illustrated in Section 3. We then used reduced form equations to understand and quantify 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 (discussed in Section 3).

2.5. Extending the CDD Calculation to Include Humidity

To extend the CDD analysis to also account for humidity, heat index-CDD was calculated similar to that of the air temperature-CDD, and geographically varying base/set-point HI estimated using the Energy Signature method, as illustrated in Figures 1b and 1d. 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

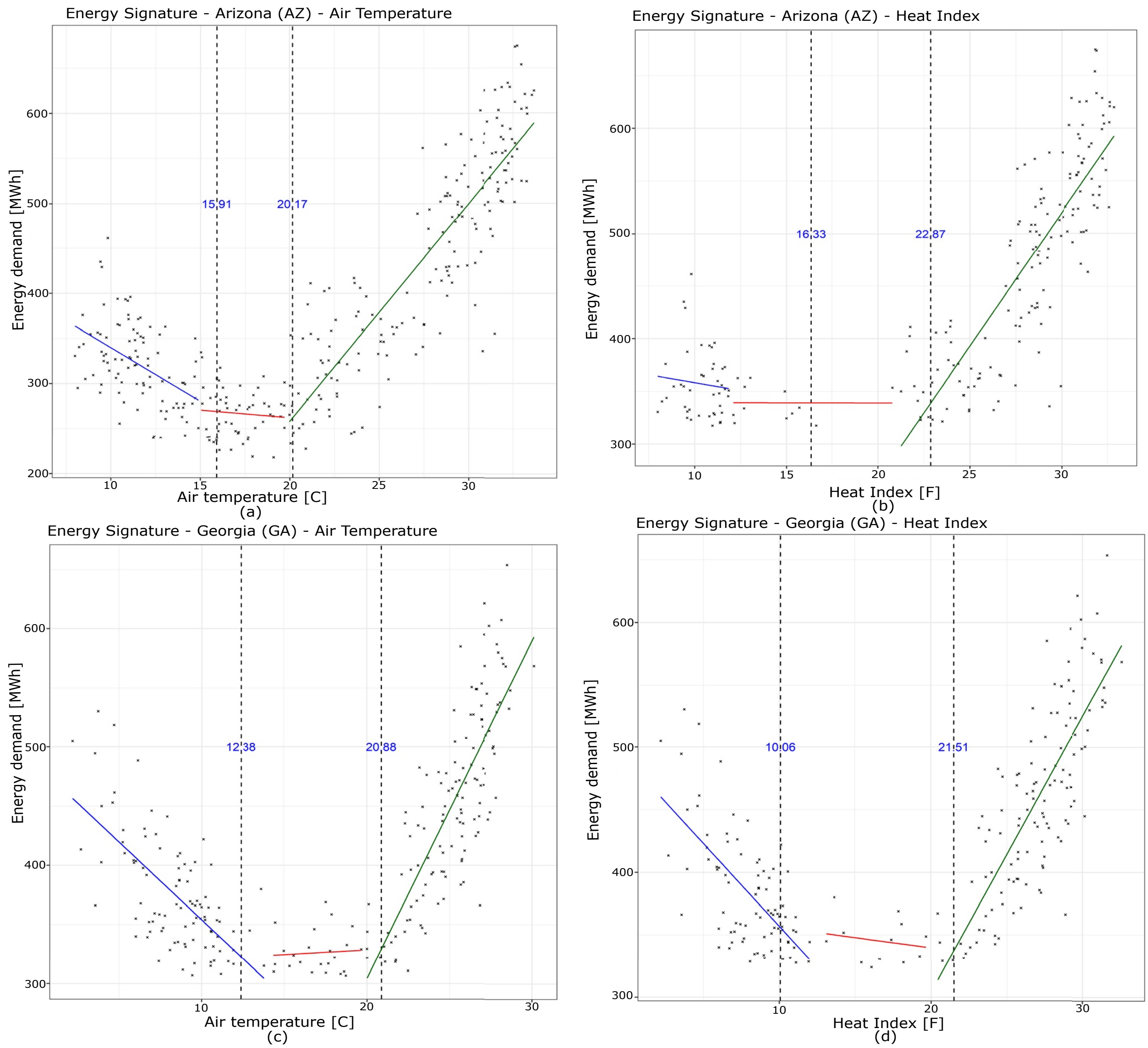

Figure 1. An example of the Energy Signature Method conducted for the state of Arizona (AZ) for air temperature-based Cooling Degree Days (CDD) (a) and heat index-based CDD (b). The example is also shown for the state of Georgia (GA) for air temperature-based CDD (c) and heat index-based CDD (d). The derived heating and cooling set-points for each state and variable are depicted in blue.

et al., 2015; Rothfusz, 1990). Characterizing the climate-sensitivity of energy demand requires accounting for the synergistic effects of air temperature and near-surface humidity on human body. Accounting for the role of humidity, therefore, is necessary for modeling energy demand profile (Maia-Silva et al., 2020). 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 is measured in degrees Fahrenheit.

Furthermore, we also analyzed the extension of conventional temperature-based CDD to another heat-stress measure based on Discomfort Index (DI) that also accounts for variability in both near-surface air temperature and humidity (Buzan et al., 2015). A recent study by (Sailor et al., 2019) demonstrated the usefulness of DI in building comfort levels. DI is estimated considering both dry-bulb and wet-bulb temperatures—the functional form and estimation approach are detailed in Buzan et al. (2015) and Maia-Silva et al. (2020).

2.6. Characterizing Air Conditioning Prevalence and Affordability

The CDD index has other applications beyond its direct use in cooling demand estimation. Specifically, CDD is used in estimating air conditioning penetration (PNT) as well as in calculating the ratio of households that could afford air conditioning ($S_{\max}$)

We extended our CDD analysis to these two widely used indices due to their relevance to human heat comfort (Jakubcionis & Carlsson, 2017; Laine et al., 2019). PNT represents the percentage of homes in a certain area that have air conditioning, and is calculated using the following equation (Laine et al., 2019).

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

Where CDD is the summation of annual CDD.

$S_{\max}$ 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.

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

The CDD here denotes the annual CDD value for a given region.

3. Results

In this section, we first summarize the results associated with deriving geographically specific CDDs. We then present the extension of the CDD calculation to also account for humidity, and discuss the associated implications under present and future climate conditions.

3.1. The CDD Base-Value Heterogeneity Across the CONUS

To test the hypothesis of whether the CDD estimates that use 65°F (18.3°C) as their base/set-point temperature adequately capture thermal comfort across the CONUS, we leverage the Energy Signature method (Bhatnagar et al., 2018; Jacobsen, 1985; Lee et al., 2013; 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 over the same time-period (NARR, 2020).

The differences between the 65°F (18.3°C) and derived optimal set-points are depicted in Figure 2a, with states shaded in orange (blue) representing CDDs with higher (lower) than 65°F (18.3°C) set-point temperatures (also see Figure 3a). 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 (Maia-Silva et al., 2020; Petri & Caldeira, 2015; also see Figure S1 in Supporting Information S1).

There are significant deviations of the derived base temperatures from the commonly used 65°F (18.3°C), with 30% of the CONUS states showing absolute variations higher than 10% (6.5°F). In Southern states, the derived 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 the estimated CDD values. Figure 2b depicts the implication of estimating CDD using the geographically

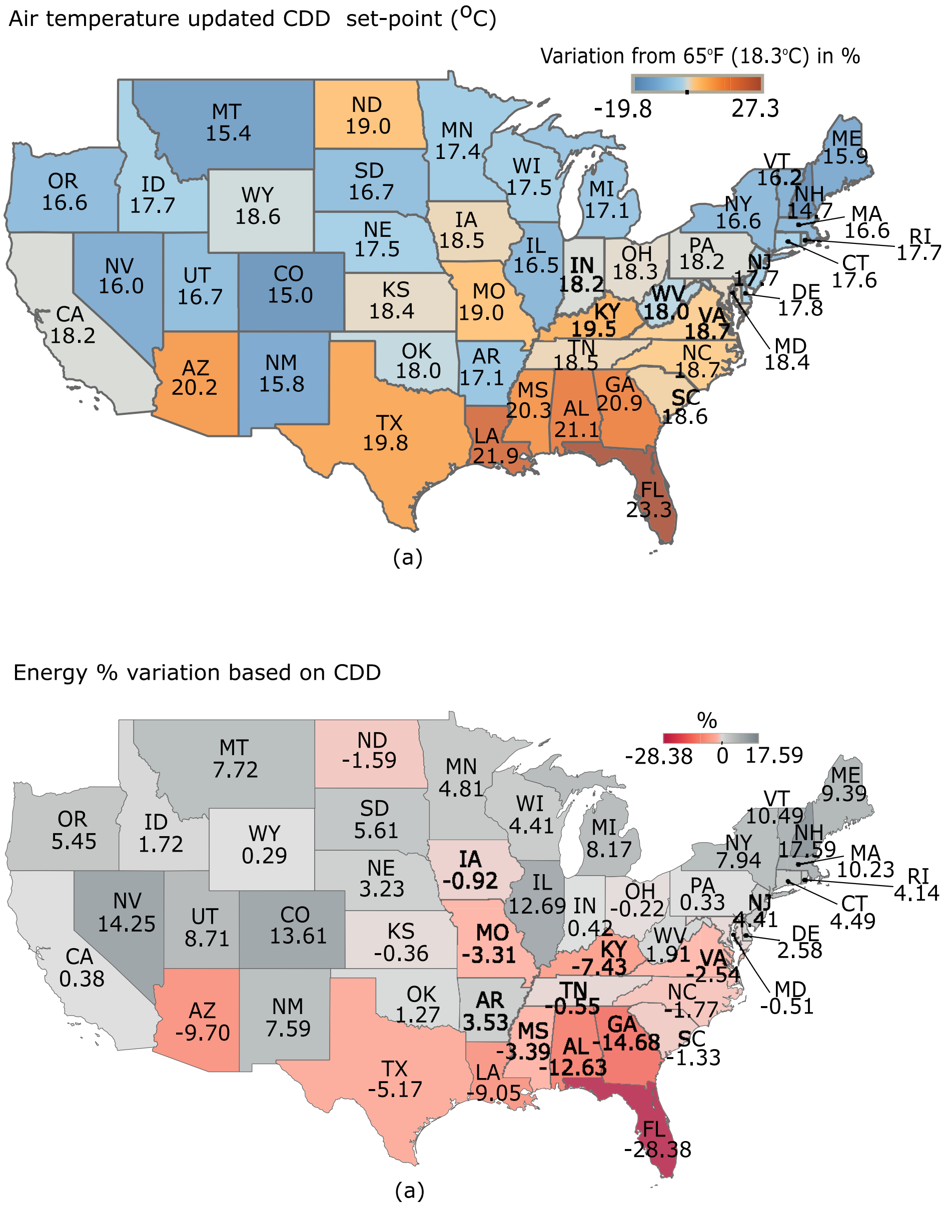

Figure 2. (a) The derived Cooling Degree Days (CDD) air temperature set-points for the CONUS states. The numbers indicated on the panel (a) represent the derived set-point temperatures, and the background colors the deviation of the set-point temperature from the traditional fixed value of 18.3°C. In 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. Here in panel (b), both indicated numbers and background colors represent the percentage change estimates.

varying set-point air temperatures. Specifically, the figure depicts the percentage shift in the climate-sensitive portion of cooling demand state-wide, with variations up to 29%. This result demonstrates that in states with negative variations (shaded in red), the conventional set-point temperature overestimates the climate-sensitive portion of the cooling demand. The overestimation has a higher absolute variation, as seen in states like Florida (FL, −28.38%) and Georgia (GA, −14.68%) which rank amongst the most energy-intensive states in the country. To illustrate the extent of these deviations, we use FL as an example. A −28.38% change in FL cooling consumption would reflect an overestimation of 4,700KWh per capita (EIA, 2020c).

States shaded in blue demonstrate areas where the use of the conventional set-point temperature in calculating CDD underestimates the climate-sensitive portion of demand. While these underestimations are comparatively

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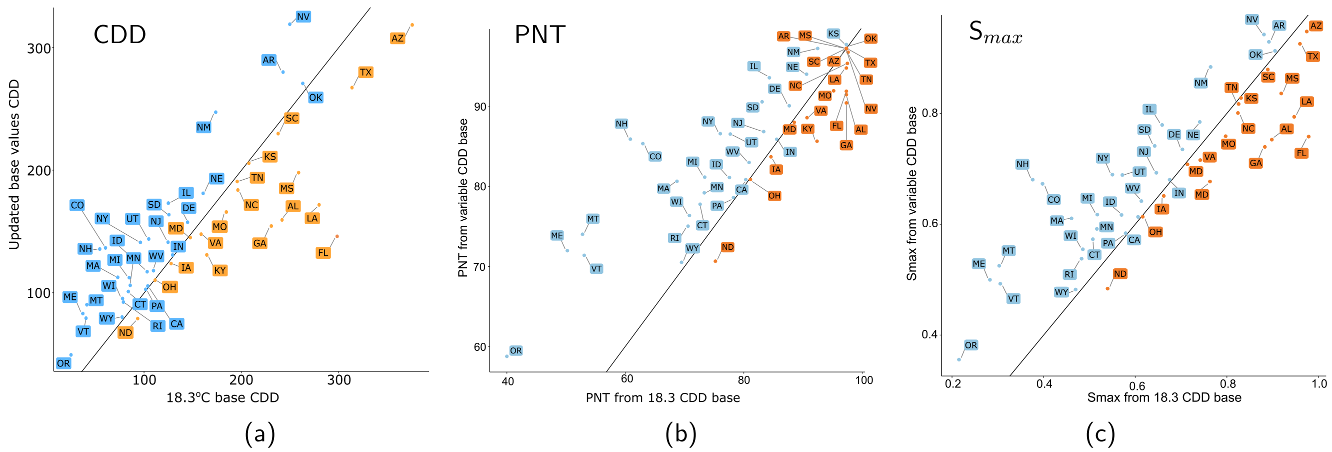

Figure 3. Scatter plots depicting the state-wide variation in: (a) Summer Cooling Degree Days (CDD) values estimated using the 18.3°C base point temperature versus the derived base point values; (b) same as (a), but for the PNT estimates (representing the percentage of homes in a certain area that have access to air conditioning); and (c) for the Smax values (representing the fraction of households in a certain area that would acquire AC if they could afford it). All three variables are average estimates corresponding to the observational time-period (1990–2016). In all three scatter plots, the respective (1:1) lines are also shown as the reference.

lower in absolute value, they have significant implications in key energy-intensive states such as Illinois (IL, 12.69%) and New York (NY, 7.94%). Moreover, the states where the conventional approach leads to an underestimation of cooling demand present serious challenges to energy planning. 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.

Besides the advantage of using geographically varying CDDs for more accurate demand forecasting, there are other benefits such as better estimation of air conditioning penetration and adoption rates. For example, the use of generic CDDs in calculating Cooling Penetration (PNT; Laine et al., 2019) and the fraction of households that would acquire AC if they could afford it (S_{max}; Jakubcionis & Carlsson, 2017; refer to Section 2.6) would yield misestimations as high as 9% and 17%, respectively (Figure 3).

The PNT estimates are also significantly affected when using the projected CDDs as well as the humidity-based CDD, as seen in Figures S2 and S3 in Supporting Information S1 (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 Figures S4 and S5 in Supporting Information S1, 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 the lack of threshold limits in its calculation (Equation 7). Nevertheless, for both indices (i.e., PNT and S_{max}) over half of the states (shaded in blue) represent significant underestimations of the projected CDD estimates (Figures 3b and 3c; see also Figures S4 and S5 in Supporting Information S1), presenting significant cause for concern in energy planning.

3.2. The Role of Near-Surface Humidity and Corresponding CDD Estimates

Considering the significant challenges posed by climate change, not only in terms of increased frequency and intensity of extreme heat events over time (Auffhammer et al., 2017; Creutzig et al., 2018; IPCC, 2014; Mehrabi et al., 2019), but also the growing importance of humidity in shaping future air conditioning demand (Bhatnagar et al., 2018; Guan, 2009; Holmes et al., 2016; Maia-Silva et al., 2020; Sailor et al., 2019), we analyze the projected changes in CDDs based on air temperature and contrast them with a similar measure based on heat index (HI), 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 method that is used for calculating air temperature-based CDDs. In other words, we estimate the geographically varying base/set-point HI 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.

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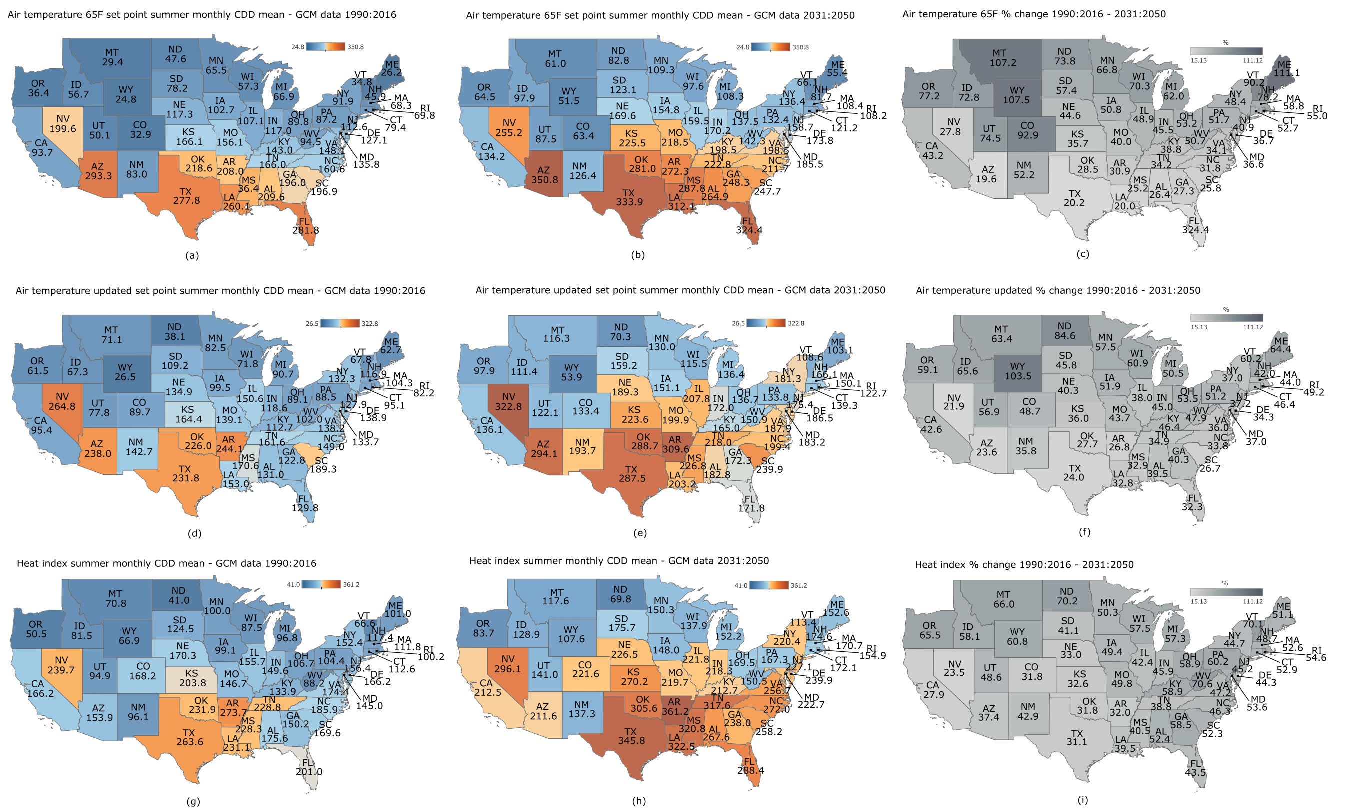

Figure 4. The top two panels represent state-level Cooling Degree Days (CDD) values estimated using air temperature with a traditional set-point value of 65°F (the top panel) and the derived set-point temperature (the middle panel). The bottom panel represents CDD for heat index. The results illustrated in (a), (d), and (g) represent data from the Global Circulation Models-based historical period (1990–2016) for summer months (May to September) for, respectively, the traditional set-point temperature, the derived air temperature, and heat index. (b), (e), and (h) represent the projected time period (2031–2050) and same summer months for the the traditional fixed set-point air temperature, derived (varying) air temperature, and heat index, respectively. Finally, figure (c), (f), and (i) depict the difference between the two previous panels for each variable (traditional air temperature, derived air temperature, and heat index).

Figures 4a and 4b show monthly summer-time CDD values using air temperature of 65°F (18.3°C) as the set-point for the historical period (1990–2016, a) and future projections (2031–2050, b), while Figures 4d and 4e demonstrate the same information when using geographically varying set-point temperature. Figures 4g and 4h reflect the same monthly summer-time CDD values for both historical and future projections for heat index (HI) based CDD. Figures 4c, 4f and 4i illustrate the percentage difference in respective CDD within each climate measure (i.e., between air temperature set-point of 65°F, geographically varying set-point air temperature, and heat index, respectively) between the historical and future time periods. In other words, they reflect the intensity that each climate measure is changing over time. Important differences in CDDs between the 65°F fixed set-point and the geographically varying set-point are seen in the southern states, such as Texas and Florida, with the 65°F fixed set-point presenting higher values of CDD (334 and 324 units, respectively). This is expected since 65°F is below the varying set-point values for these states, leading to a possible overestimation in CDD values. When comparing to heat index for the future projected scenario (Figure 4h) there is a great general increase for the same areas, showing the important role of humidity in the southern region of the country. California, a crucial state in terms of energy consumption, population, and revenue, presents a dramatic change in HI based CDD measure compared to air temperature based CDD, with a higher monthly CDD (213 units), showing the potential for underestimation when only focusing on air temperature CDDs, either the updated varying values or the convention fixed set-point values. This is in line with previous research (Kumar et al., 2020) that showed a strong asymmetrical effect of heat-stress measure (that accounts for both humidity and air temperature) on electricity demand in California.

Heat index is used in this study as it is a widely used indicator of heat-stress (Buzan et al., 2015). Having said that, a comprehensive analysis of the role of humidity through an extensive analysis of other measures of heat stress is necessary to identify the optimal heat-stress measure for each state (Maia-Silva et al., 2020). However, the goal in this study is to simply exemplify how humidity-related measures change differently over time when compared to air temperature alone, both fixed 65°F set-point and derived (varying) set-point values, and the possible misestimations that result from these differences. Additionally, we illustrate the importance of extending the CDD methodology beyond air temperature for more accurate energy-climate nexus analysis, using heat index as an example. Moreover, to check the robustness of the implications of the result, we also applied the CDD method to another widely adopted heat-stress measure of discomfort index (Guan, 2009; Holmes et al., 2016; Sailor et al., 2019). Results are shown in Figure S6 in Supporting Information S1. These results also indicate the substantial differences in projected CDD based on discomfort index compared to air temperature alone based CDDs. In summary, by illustrating these examples, we highlight the crucial role of accounting for humidity in the climate-energy nexus research.

4. Discussion and Concluding Remarks

Increased demand for cooling has been identified as a critical blind spot in today's sustainability discourse (Khosla et al., 2020). 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; Isaac & van Vuuren, 2009; Li et al., 2020). Despite its widespread use in characterizing human thermal comfort, CDD is not a universally reliable proxy for cooling energy demand.

Here, we examine the consequences of calculating CDD based on the widely used generic set-point temperature of 65°F (18.3°C) in energy infrastructure planning. Specifically, we use the historical summer-time energy demand data to derive geographically specific comfort-zone temperatures across the CONUS. We demonstrate the degree to which generic CDDs over- or underestimate demand for cooling by disregarding geographical heterogeneity in thermal comfort across the country. Moreover, we extend the calculation of CDD to also account for humidity and 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 credit 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 (De Angelis et al., 2017; Fu et al., 2020; 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; Melaas et al., 2016; Susca et al., 2011).

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 mis-estimation of projected energy demand under climate change, with considerable implications for the security of the grid. Overall, the insights and findings of our study contribute to pushing the sustainable development agenda and efforts in delivering sustainable cooling to society.

Data Availability Statement

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; CIESIN, 2019; Mesinger et al., 2006; NCEP, 2019), and CMIP5 model outputs through the Earth System Grid Federation (ESGF) gateways.

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