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

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

[1]UFZ-Helmholtz Centre for Environmental Research
[2]Purdue University

March 31, 2021

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.

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:

- The analysis of historical electricity demand shows that the widely used CDD estimates fall short (±25%) 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 conditions.
- A singular focus on air-temperature based CDD with a generic set-point temperature undermines grid resilience during extreme heat events.

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 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 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 comfort zones across different geographic areas in the U.S. 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., 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 three-fold 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; Lebassi et al., 2010; Deroubaix et al., 2021). 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; 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 – which is 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).

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. 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; Pokhrel et al., 2018; Ortiz et al., 2018; Angeles et al., 2018). 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[1], 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 American 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 (Buzan et al., 2015; Anderson G. Brooke et al., 2013; Willett & Sherwood, 2012; Maia-

[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.

Silva et al., 2020) – 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 kilometer spatial resolution (Mesinger et al., 2006; NCEP, 2019; CIESIN, 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 dataset (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 (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 the 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 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 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 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 high greenhouse emission levels (Taylor et al., 2012; Warszawski et al., 2014; Nateghi & Mukherjee, 2017). 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 (Kumar et al., 2020; Biardeau 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 (van Ruijven et al., 2019; Mukherjee et al., 2018; Auffhammer et al., 2017), we de-trended the raw, state-level electricity consumption data. There are various different de-trending approaches in the literature (Bessec & Fouquau, 2008). The method used in this study (Sailor & Muñoz, 1997) is based on one the most widely-used approaches in the climate-energy research literature and its effectiveness has been extensively documented (Khoshbakht et al., 2018; Santágata et al., 2017; Parkinson & Djilali, 2015; Brown et al., 2016; Alipour et al., 2019; Mukherjee & Nateghi, 2017a). 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 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, the CDD for a given 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 CDD is usually aggregated to annual, seasonal, or monthly levels by summing 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 (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. 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 under climate change to also account for humidity, heat index-CDD was calculated using the Energy Signature method using observational and climate projections data records, as illustrated in Figures 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. 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 analysed 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 Cooling Degree Day (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 (Smax).

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

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

The CDD here denotes the annual CDD value for the 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 point temperature adequately capture 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 (also see Figure 3(a)). 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; Maia-Silva et al., 2020)(also see Supplementary Figure 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 2(b) depicts the implication of estimating CDD using the derived set pint 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 Florida 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 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-specific 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) (S. 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 Supplementary Figures 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 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 (Fig. 3 (b) and (c); see also Supplementary Figs. S4 and S5), 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 (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; Sailor et al., 2019; Guan, 2009; Holmes et al., 2016), 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 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.

Figure 4(a) and Figure 4(b) 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 Figure 4(d) and Figure 4(e) demonstrate the same information when using derived temperature set-points. Figure 4(g) and Figure 4(h) reflect the same monthly summer-time CDD values for both historical and future projections for heat index. Figure 4(c), Figure 4(f), and Figure 4(i) illustrate the percentage difference within each climate measure (i.e., between air temperature set-point of 65°F , derived air temperature set-points, 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 between the 65°F air temperature and the updated set-point are seen in the southern states, such as Texas and Florida, with the 65°F set-point presenting higher values of CDD (334 and 324 units, respectively). This is expected since 65°F is below the derived 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 4(h)) 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 humidity 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 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 was 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, both 65°F set-point and derived 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 (Sailor et al., 2019; Guan, 2009; Holmes et al., 2016). Results are shown in Supplementary Figure S6. These results also indicate the substantial differences in projected CDD based on discomfort index compared to temperature 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., 2020a). Inadequate characterization of human thermal comfort poses significant challenges to the security and resilience of the grid and present obstacles to achieving sustainable development goals (SDGs) (Biardeau et al., 2020; Li et al., 2020; Isaac & van Vuuren, 2009). 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 (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 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.

5 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.

Acknowledgments

The authors gratefully acknowledge the Purdue Climate Change Research Center, the Center for the Environment at Purdue University as well as the NSF CMMI-1826161. The authors are grateful to the ISI-MIP project for providing the GCM-based climate projection data used in this study. The ISI-MIP project was funded by the German Federal Ministry of Education and Research (BMBF) with project funding reference number 01LS1201A. The authors would also like to acknowledge the World Climate Research Programme's Working Group on Coupled Modelling for the CMIP5 simulations.

References

Alipour, P., Mukherjee, S., & Nateghi, R. (2019). Assessing climate sensitivity of peak electricity load for resilient power systems planning and operation: A study applied to the texas region. *Energy*, *185*, 1143–1153.

Anderson G. Brooke, Bell Michelle L., & Peng Roger D. (2013, October). Methods to Calculate the Heat Index as an Exposure Metric in Environmental

Health Research. *Environmental Health Perspectives*, *121*(10), 1111–1119. doi: 10.1289/ehp.1206273

Angeles, M. E., González, J. E., & Ramírez, N. (2018, July). Impacts of climate change on building energy demands in the intra-Americas region. *Theoretical and Applied Climatology*, *133*(1), 59–72. doi: 10.1007/s00704-017-2175-9

Auffhammer, M., Baylis, P., & Hausman, C. H. (2017, February). Climate change is projected to have severe impacts on the frequency and intensity of peak electricity demand across the United States. *Proceedings of the National Academy of Sciences of the United States of America*, *114*(8), 1886–1891. doi: 10.1073/pnas.1613193114

Berger, M. W. (2004). *Cool comfort: America's romance with air-conditioning.* JSTOR.

Bessec, M., & Fouquau, J. (2008, September). The non-linear link between electricity consumption and temperature in Europe: A threshold panel approach. *Energy Economics*, *30*(5), 2705-2721. doi: 10.1016/j.eneco.2008.02.003

Bhatnagar, M., Mathur, J., & Garg, V. (2018, July). Determining base temperature for heating and cooling degree-days for India. *Journal of Building Engineering*, *18*, 270–280. doi: 10.1016/j.jobe.2018.03.020

Biardeau, L. T., Davis, L. W., Gertler, P., & Wolfram, C. (2020, January). Heat exposure and global air conditioning. *Nature Sustainability*, *3*(1), 25–28. doi: 10.1038/s41893-019-0441-9

Birol, F. (2018). The future of cooling: opportunities for energy-efficient air conditioning. *International Energy Agency*.

Borunda, A. (2020, August). *Why renewables aren't to blame for California's blackouts.* https://www.nationalgeographic.com/science/2020/08/why-renewables-arent-reason-california-blackouts/.

Bounoua, L., Zhang, P., Mostovoy, G., Thome, K., Masek, J., Imhoff, M., … Toure, A. M. (2015, August). Impact of urbanization on US surface climate. *Environmental Research Letters*, *10*(8), 084010. doi: 10.1088/1748-9326/10/8/084010

Brown, M. A., Cox, M., Staver, B., & Baer, P. (2014). Climate Change and Energy Demand in Buildings. *Proceedings of the American Council for an Energy Efficient Economy (ACEEE) Summer Study on Energy Efficiency in Buildings*, 13.

Brown, M. A., Cox, M., Staver, B., & Baer, P. (2016, January). Modeling climate-driven changes in U.S. buildings energy demand. *Climatic Change*, *134*(1), 29–44. doi: 10.1007/s10584-015-1527-7

Buzan, J. R., Oleson, K., & Huber, M. (2015). Implementation and comparison of a suite of heat stress metrics within the Community Land Model version 4.5. *Geoscientific Model Development; Katlenburg-Lindau*, *8*(2), 151. doi: http://dx.doi.org/10.5194/gmd-8-151-2015

CIESIN. (2019). *Center for International Earth Science Information Network.* Retrieved 2019-01-31, from `http://www.ciesin.org/data.html`

Coumou, D., & Rahmstorf, S. (2012, July). A decade of weather extremes. *Nature Climate Change*, *2*(7), 491–496. doi: 10.1038/nclimate1452

Creutzig, F., Roy, J., Lamb, W. F., Azevedo, I. M. L., Bruine de Bruin, W., Dalkmann, H., … Weber, E. U. (2018, April). Towards demand-side solutions for mitigating climate change. *Nature Climate Change*, *8*(4), 260–263. doi: 10.1038/s41558-018-0121-1

Davis, L. W., & Gertler, P. J. (2015, May). Contribution of air conditioning adoption to future energy use under global warming. *Proceedings of the National Academy of Sciences*, *112*(19), 5962–5967. doi: 10.1073/pnas.1423558112

Day, T. (2006). *Degree-days : theory and application - tm41: 2006.*

De Angelis, A., Saro, O., & Truant, M. (2017, September). Evaporative cooling systems to improve internal comfort in industrial buildings. *Energy Procedia*, *126*, 313–320. doi: 10.1016/j.egypro.2017.08.245

Deroubaix, A., Labuhn, I., Camredon, M., Gaubert, B., Monerie, P.-A., Popp, M., . . . Siour, G. (2021). Large uncertainties in trends of energy demand for heating and cooling under climate change. *Nature Communications*, *12*(1), 1–8.

EIA. (2020a). *Annual Energy Outlook 2020.* https://www.eia.gov/outlooks/aeo/.

EIA. (2020b). *Electric power sales, revenue, and energy efficiency Form EIA-861 detailed data files.* https://www.eia.gov/electricity/data/eia861/.

EIA. (2020c). *Florida - State Energy Profile Overview - U.S. Energy Information Administration (EIA).* https://www.eia.gov/state/?sid=FL.

Fu, S. C., Zhong, X. L., Zhang, Y., Lai, T. W., Chan, K. C., Lee, K. Y., & Chao, C. Y. H. (2020, October). Bio-inspired cooling technologies and the applications in buildings. *Energy and Buildings*, *225*, 110313. doi: 10.1016/j.enbuild.2020.110313

Goldstein, B., Gounaridis, D., & Newell, J. P. (2020, August). The carbon footprint of household energy use in the United States. *Proceedings of the National Academy of Sciences*, *117*(32), 19122–19130. doi: 10.1073/pnas.1922205117

Guan, L. (2009). Preparation of future weather data to study the impact of climate change on buildings. *Building and Environment*, *44*(4), 793–800.

Hempel, S., Frieler, K., Warszawski, L., Schewe, J., & Piontek, F. (2013). A trend-preserving bias correction – The ISI-MIP approach. *Earth System Dynamics*, *4*(2), 219–236. doi: 10.5194/esd-4-219-2013

Holmes, S. H., Phillips, T., & Wilson, A. (2016, January). Overheating and passive habitability: Indoor health and heat indices. *Building Research & Information*, *44*(1), 1–19. doi: 10.1080/09613218.2015.1033875

Hulley, G. C., Dousset, B., & Kahn, B. H. (2020). Rising Trends in Heatwave Metrics Across Southern California. *Earth's Future*, *8*(7), e2020EF001480. doi: 10.1029/2020EF001480

IEA. (2008). *The Future of Cooling – Analysis.* https://www.iea.org/reports/the-future-of-cooling.

IPCC. (2014). *Fifth Assessment Report – IPCC.*

Isaac, M., & van Vuuren, D. P. (2009, February). Modeling global residential sector energy demand for heating and air conditioning in the context of climate change. *Energy Policy*, *37*(2), 507–521. doi: 10.1016/j.enpol.2008.09.051

Jacobsen, F. (1985). Energy signature and energy monitoring in building energy management systems. *Proceeding of CLIMA 2000 world congress*, *3*.

Jacobsen, F. R. (1985). Energy signature and energy monitoring in building energy management systems. In *Proceeding of clima 2000 world congress* (Vol. 3, pp. 25–31).

Jaglom, W. S., McFarland, J. R., Colley, M. F., Mack, C. B., Venkatesh, B., Miller, R. L., . . . Kayin, S. (2014, October). Assessment of projected temperature impacts from climate change on the U.S. electric power sector using the Integrated Planning Model. *Energy Policy*, *73*, 524–539. doi: 10.1016/j.enpol.2014.04.032

Jakubcionis, M., & Carlsson, J. (2017, February). Estimation of European Union residential sector space cooling potential. *Energy Policy*, *101*, 225–235. doi: 10.1016/j.enpol.2016.11.047

Khan, Z., Iyer, G., Patel, P., Kim, S., Hejazi, M., Burleyson, C., & Wise, M. (2021, March). Impacts of long-term temperature change and variability on electricity investments. *Nature Communications*, *12*(1), 1643. doi: 10.1038/s41467-021-21785-1

Khoshbakht, M., Gou, Z., & Dupre, K. (2018, April). Energy use characteristics and benchmarking for higher education buildings. *Energy and Buildings*, *164*, 61–76. doi: 10.1016/j.enbuild.2018.01.001

Khosla, R., Miranda, N. D., Trotter, P. A., Mazzone, A., Renaldi, R., McElroy, C., . . . McCulloch, M. (2020a). Cooling for sustainable development. *Nature*

Sustainability, 1–8.
Khosla, R., Miranda, N. D., Trotter, P. A., Mazzone, A., Renaldi, R., McElroy, C., … McCulloch, M. (2020b, October). Cooling for sustainable development. *Nature Sustainability*, 1–8. doi: 10.1038/s41893-020-00627-w
Kumar, R., Rachunok, B., Maia-Silva, D., & Nateghi, R. (2020, July). Asymmetrical response of California electricity demand to summer-time temperature variation. *Scientific Reports*, *10*(1), 10904. doi: 10.1038/s41598-020-67695-y
Lebassi, B., González, J. E., Fabris, D., & Bornstein, R. (2010, June). Impacts of Climate Change in Degree Days and Energy Demand in Coastal California. *Journal of Solar Energy Engineering*, *132*(031005). doi: 10.1115/1.4001564
Lee, K., Baek, H.-J., & Cho, C. (2013, September). The Estimation of Base Temperature for Heating and Cooling Degree-Days for South Korea. *Journal of Applied Meteorology and Climatology*, *53*(2), 300–309. doi: 10.1175/JAMC-D-13-0220.1
Li, D., Yuan, J., & Kopp, R. E. (2020, May). Escalating global exposure to compound heat-humidity extremes with warming. *Environmental Research Letters*, *15*(6), 064003. doi: 10.1088/1748-9326/ab7d04
Maia-Silva, D., Kumar, R., & Nateghi, R. (2020, April). The critical role of humidity in modeling summer electricity demand across the United States. *Nature Communications*, *11*(1), 1686. doi: 10.1038/s41467-020-15393-8
McGregor, G. R., Bessmoulin, P., Ebi, K., & Menne, B. (2015). *Heatwaves and health: guidance on warning-system development.* WMOP.
Mehrabi, Z., Donner, S., Rios, P., Guha-Sapir, D., Rowhani, P., Kandlikar, M., & Ramankutty, N. (2019, June). Can we sustain success in reducing deaths to extreme weather in a hotter world? *World Development Perspectives*, *14*, 100107. doi: 10.1016/j.wdp.2019.02.018
Melaas, E. K., Wang, J. A., Miller, D. L., & Friedl, M. A. (2016, May). Interactions between urban vegetation and surface urban heat islands: A case study in the Boston metropolitan region. *Environmental Research Letters*, *11*(5), 054020. doi: 10.1088/1748-9326/11/5/054020
Mesinger, F., DiMego, G., Kalnay, E., Mitchell, K., Shafran, P. C., Ebisuzaki, W., … Shi, W. (2006). North american regional reanalysis. *Bulletin of the American Meteorological Society*, *87*(3), 343-360. doi: 10.1175/BAMS-87-3-343
Mukherjee, S., & Nateghi, R. (2017a, June). Climate sensitivity of end-use electricity consumption in the built environment: An application to the state of Florida, United States. *Energy*, *128*, 688–700. doi: 10.1016/j.energy.2017.04.034
Mukherjee, S., & Nateghi, R. (2017b). A Data-Driven Approach to Assessing Supply Inadequacy Risks Due to Climate-Induced Shifts in Electricity Demand. *Risk Analysis*, *0*(0). doi: 10.1111/risa.13192
Mukherjee, S., Nateghi, R., & Hastak, M. (2018, July). A multi-hazard approach to assess severe weather-induced major power outage risks in the U.S. *Reliability Engineering & System Safety*, *175*, 283–305. doi: 10.1016/j.ress.2018.03.015
Mukhopadhyay, S., & Nateghi, R. (2017, July). Estimating climate — Demand Nexus to support longterm adequacy planning in the energy sector. In *2017 IEEE Power Energy Society General Meeting* (pp. 1–5). doi: 10.1109/PESGM.2017.8274648
NARR. (2020). *ESRL : PSD : NCEP North American Regional Reanalysis (NARR).* https://www.esrl.noaa.gov/psd/data/gridded/data.narr.html.
Nateghi, R., & Mukherjee, S. (2017, November). A multi-paradigm framework to assess the impacts of climate change on end-use energy demand. *PLOS ONE*, *12*(11), e0188033. doi: 10.1371/journal.pone.0188033
NCEP. (2019). *NCEP North American Regional Reanalysis (NARR).* Retrieved 2019-01-31, from `https://www.esrl.noaa.gov/psd/data/gridded/data.narr.html`

Nie, X., Yoo, Y., Hewakuruppu, H., Sullivan, J., Krishna, A., & Lee, J. (2020, April). Cool White Polymer Coatings based on Glass Bubbles for Buildings. *Scientific Reports*, *10*(1), 6661. doi: 10.1038/s41598-020-63027-2

Obringer, R., Kumar, R., & Nateghi, R. (2019, October). Analyzing the climate sensitivity of the coupled water-electricity demand nexus in the Midwestern United States. *Applied Energy*, *252*, 113466. doi: 10.1016/j.apenergy.2019.113466

Obringer, R., Kumar, R., & Nateghi, R. (2020). Managing the water–electricity demand nexus in a warming climate. *Climatic Change*, *159*(2), 233–252.

Obringer, R., Mukherjee, S., & Nateghi, R. (2020, March). Evaluating the climate sensitivity of coupled electricity-natural gas demand using a multivariate framework. *Applied Energy*, *262*, 114419. doi: 10.1016/j.apenergy.2019.114419

Ortiz, L., González, J. E., & Lin, W. (2018, August). Climate change impacts on peak building cooling energy demand in a coastal megacity. *Environmental Research Letters*, *13*(9), 094008. doi: 10.1088/1748-9326/aad8d0

Parkinson, S. C., & Djilali, N. (2015, June). Robust response to hydro-climatic change in electricity generation planning. *Climatic Change*, *130*(4), 475–489. doi: 10.1007/s10584-015-1359-5

Petri, Y., & Caldeira, K. (2015a, August). Impacts of global warming on residential heating and cooling degree-days in the United States. *Scientific Reports*, *5*(1), 12427. doi: 10.1038/srep12427

Petri, Y., & Caldeira, K. (2015b, August). Impacts of global warming on residential heating and cooling degree-days in the United States. *Scientific Reports*, *5*(1), 12427. doi: 10.1038/srep12427

Pokhrel, R., Ortiz, L. E., Ramírez-Beltran, N. D., & González, J. E. (2018, October). On the Climate Variability and Energy Demands for Indoor Human Comfort Levels in a Tropical-Coastal Urban Environment. *Journal of Solar Energy Engineering*, *141*(031002). doi: 10.1115/1.4041401

Raymond, C., Matthews, T., & Horton, R. M. (2020, May). The emergence of heat and humidity too severe for human tolerance. *Science Advances*, *6*(19), eaaw1838. doi: 10.1126/sciadv.aaw1838

Reyna, J. L., & Chester, M. V. (2017, May). Energy efficiency to reduce residential electricity and natural gas use under climate change. *Nature Communications*, *8*(1), 1–12. doi: 10.1038/ncomms14916

Rothfusz, L. P. (1990). The heat index equation. *National Weather Service Technical Attachment (SR 90–23).*

Sailor, D. J. (2001, July). Relating residential and commercial sector electricity loads to climate—evaluating state level sensitivities and vulnerabilities. *Energy*, *26*(7), 645–657. doi: 10.1016/S0360-5442(01)00023-8

Sailor, D. J., Baniassadi, A., O'Lenick, C. R., & Wilhelmi, O. V. (2019, May). The growing threat of heat disasters. *Environmental Research Letters*, *14*(5), 054006. doi: 10.1088/1748-9326/ab0bb9

Sailor, D. J., & Muñoz, J. R. (1997, October). Sensitivity of electricity and natural gas consumption to climate in the U.S.A. – Methodology and results for eight states. *Energy*, *22*(10), 987–998. doi: 10.1016/S0360-5442(97)00034-0

Santágata, D. M., Castesana, P., Rössler, C. E., & Gómez, D. R. (2017, July). Extreme temperature events affecting the electricity distribution system of the metropolitan area of Buenos Aires (1971–2013). *Energy Policy*, *106*, 404–414. doi: 10.1016/j.enpol.2017.04.006

Schlenker, W., & Roberts, M. J. (2009). Nonlinear temperature effects indicate severe damages to U.S. crop yields under climate change. *Proceedings of the National Academy of Sciences*, *106*(37), 15594-15598. doi: 10.1073/pnas.0906865106

Shin, M., & Do, S. L. (2016, January). Prediction of cooling energy use in buildings using an enthalpy-based cooling degree days method in a hot and humid climate. *Energy and Buildings*, *110*, 57–70. doi: 10.1016/j.enbuild.2015.10.035

Sivak, M. (2009, April). Potential energy demand for cooling in the 50 largest metropolitan areas of the world: Implications for developing countries. *Energy Policy*, *37*(4), 1382–1384. doi: 10.1016/j.enpol.2008.11.031

S. Laine, H., Salpakari, J., E. Looney, E., Savin, H., Marius Peters, I., & Buonassisi, T. (2019). Meeting global cooling demand with photovoltaics during the 21st century. *Energy & Environmental Science*, *12*(9), 2706–2716. doi: 10.1039/C9EE00002J

Susca, T., Gaffin, S. R., & Dell'Osso, G. R. (2011, August). Positive effects of vegetation: Urban heat island and green roofs. *Environmental Pollution*, *159*(8), 2119–2126. doi: 10.1016/j.envpol.2011.03.007

Taylor, K. E., Stouffer, R. J., & Meehl, G. A. (2012). An overview of cmip5 and the experiment design. *Bulletin of the American meteorological Society*, *93*(4), 485–498.

van Ruijven, B. J., Cian, E. D., & Wing, I. S. (2019, June). Amplification of future energy demand growth due to climate change. *Nature Communications*, *10*(1), 2762. doi: 10.1038/s41467-019-10399-3

Waite, M., Cohen, E., Torbey, H., Piccirilli, M., Tian, Y., & Modi, V. (2017, May). Global trends in urban electricity demands for cooling and heating. *Energy*, *127*, 786–802. doi: 10.1016/j.energy.2017.03.095

Warszawski, L., Frieler, K., Huber, V., Piontek, F., Serdeczny, O., & Schewe, J. (2014). The Inter-Sectoral Impact Model Intercomparison Project (ISI – MIP): Project framework. *Proceedings of the National Academy of Sciences*, *111*(9), 3228–3232. doi: 10.1073/pnas.1312330110

Willett, K. M., & Sherwood, S. (2012). Exceedance of heat index thresholds for 15 regions under a warming climate using the wet-bulb globe temperature. *International Journal of Climatology*, *32*(2), 161–177. doi: 10.1002/joc.2257

Zmeureanu, R., & Renaud, G. (2008). Estimation of potential impact of climate change on the heating energy use of existing houses. *Energy Policy*, *36*(1), 303–310.

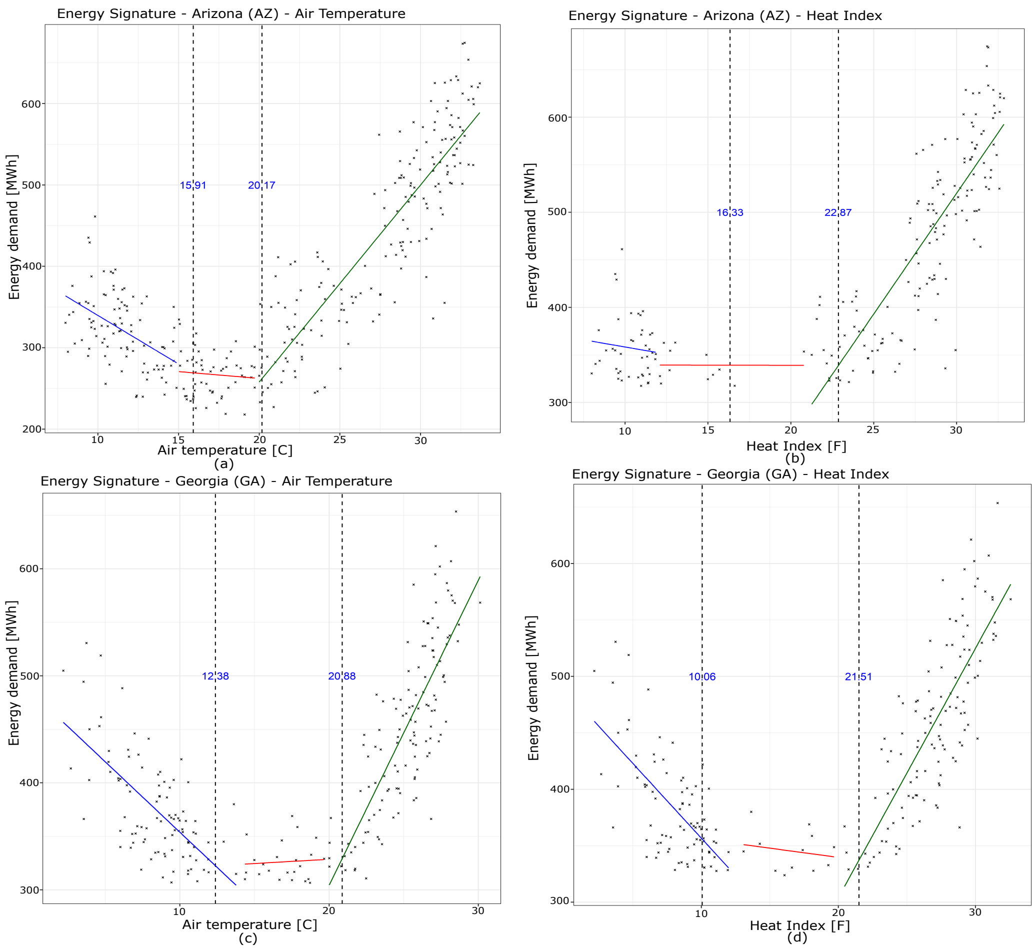

Figure 1. An example of the Energy Signature Method conducted for the state of Arizona (AZ) for air temperature-based CDD (a) and heat index-based CDD (b). The example is also shown for the state of Georgia (GA) for air temperature-based CDD (c) and heat index-based CDD (d). The derived heating and cooling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

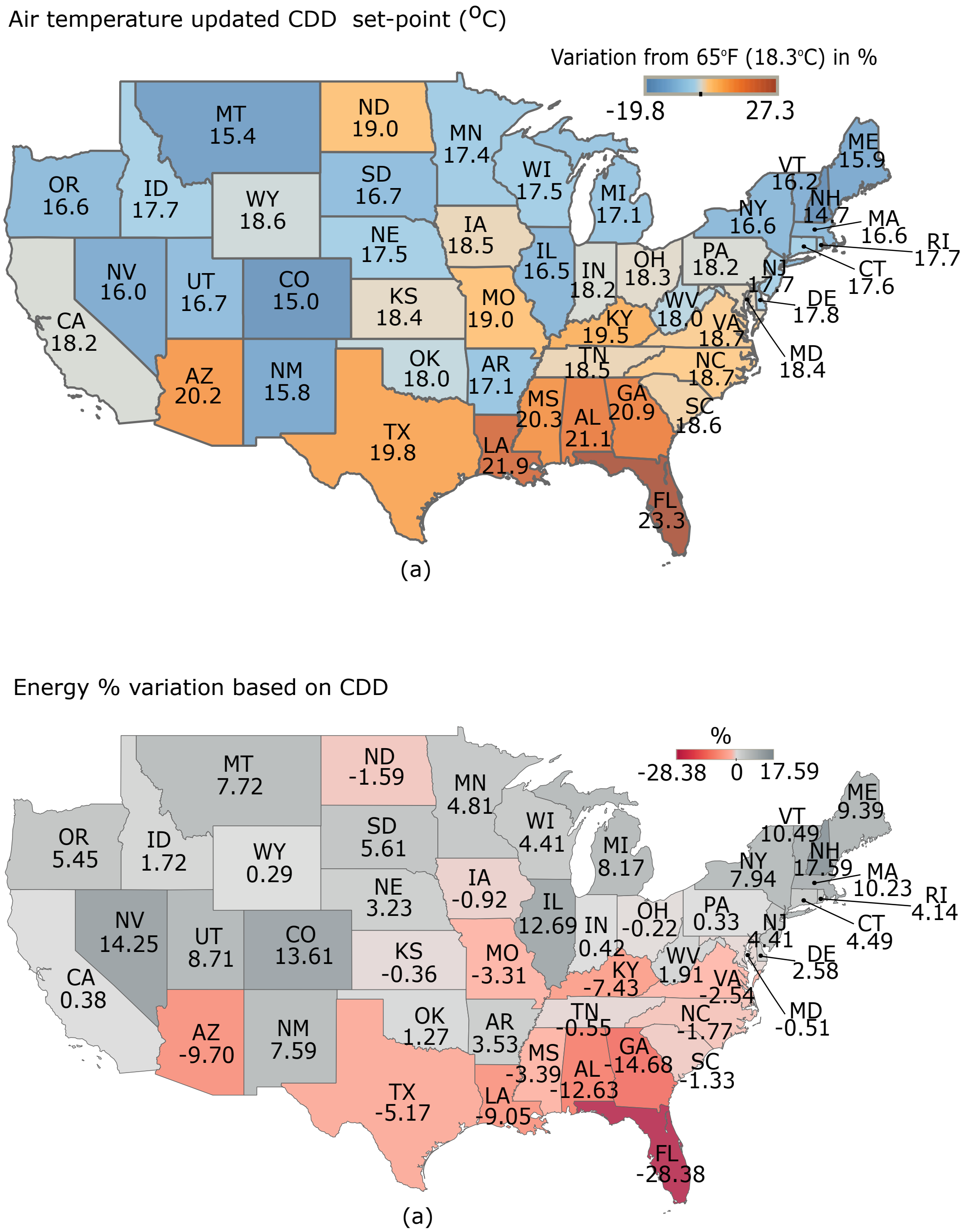

Figure 2. (a) The derived CDD air temperature set-points for the CONUS states. The numbers indicated on the panel (a) represent the derived set-point temperatures, and the background colors the deviation of the set-point temperature from the traditional fixed value of 18.3°C. In orange (blue), the darker 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.

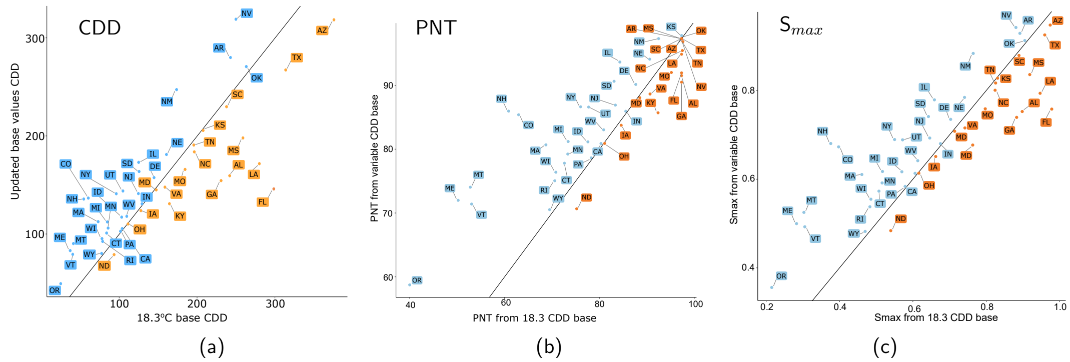

Figure 3. Scatter plots depicting the state-wide variation in: (a) Summer CDD values estimated using the 18.3°C base point temperature vs. the derived base point values; (b) same as (a), but for the PNT estimates (representing the percentage of homes in a certain area that have access to air conditioning); 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.

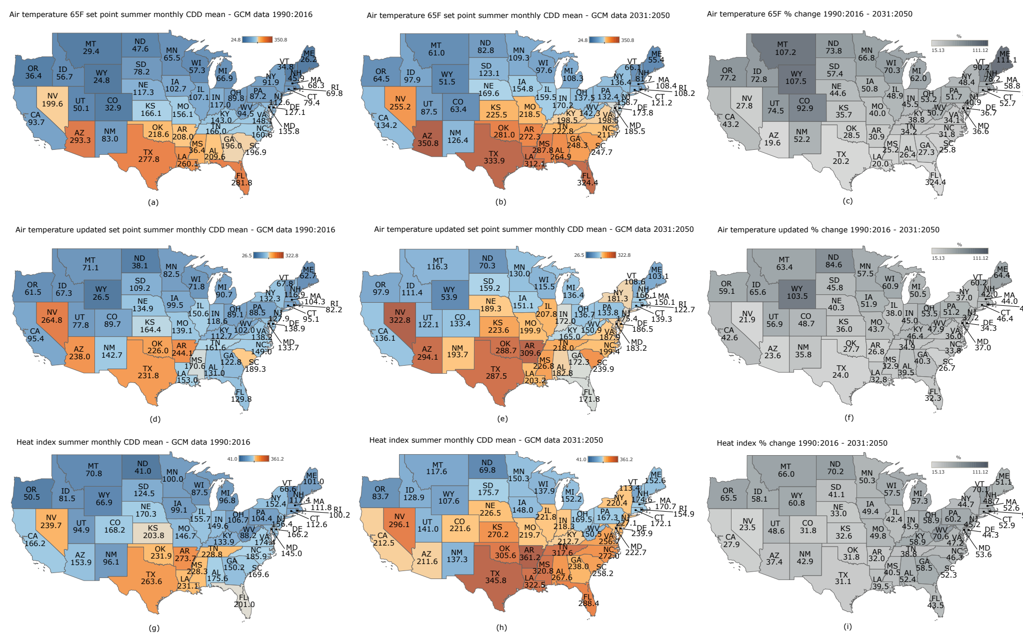

Figure 4. The top two panels represent state-level CDD values estimated using air temperature with a traditional set-point value of 65°F (the top panel) and the derived set-point temperature (the middle panel). The bottom panel represents CDD for heat index. The results illustrated in (a), (d), and (g) represent data from the GCMs-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 set-point temperature, derived 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).

Supporting Information for "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]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

Here we present supplementary Figures (S1–S6) that are cited in the main text.

Contents of this file

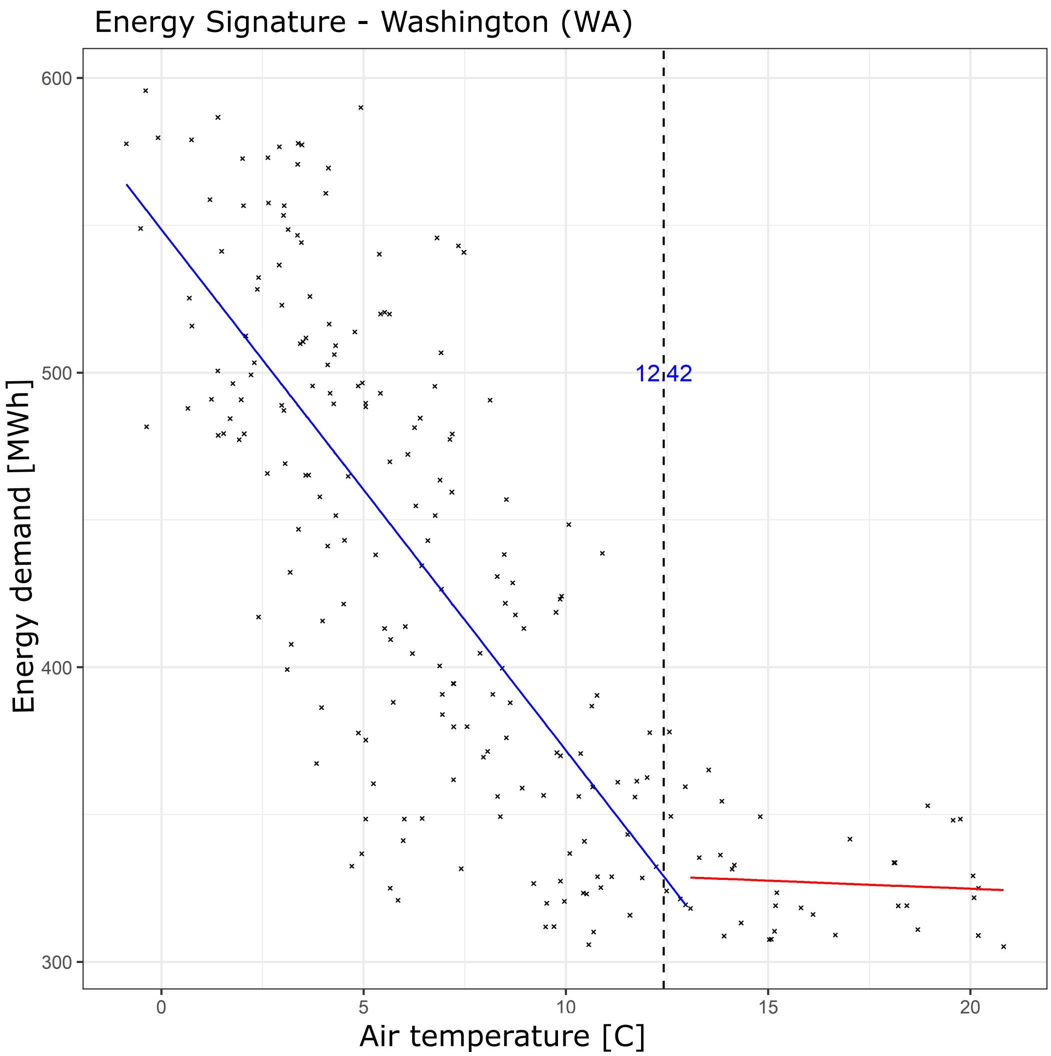

Figure S1. The Energy Signature method for the state of Washington (WA). Even though there is a energy response for the heating demand, there is no visible response for the cooling demand. Hence, we did not add WA results for the derived air temperature results depicted in the main Figure 1.

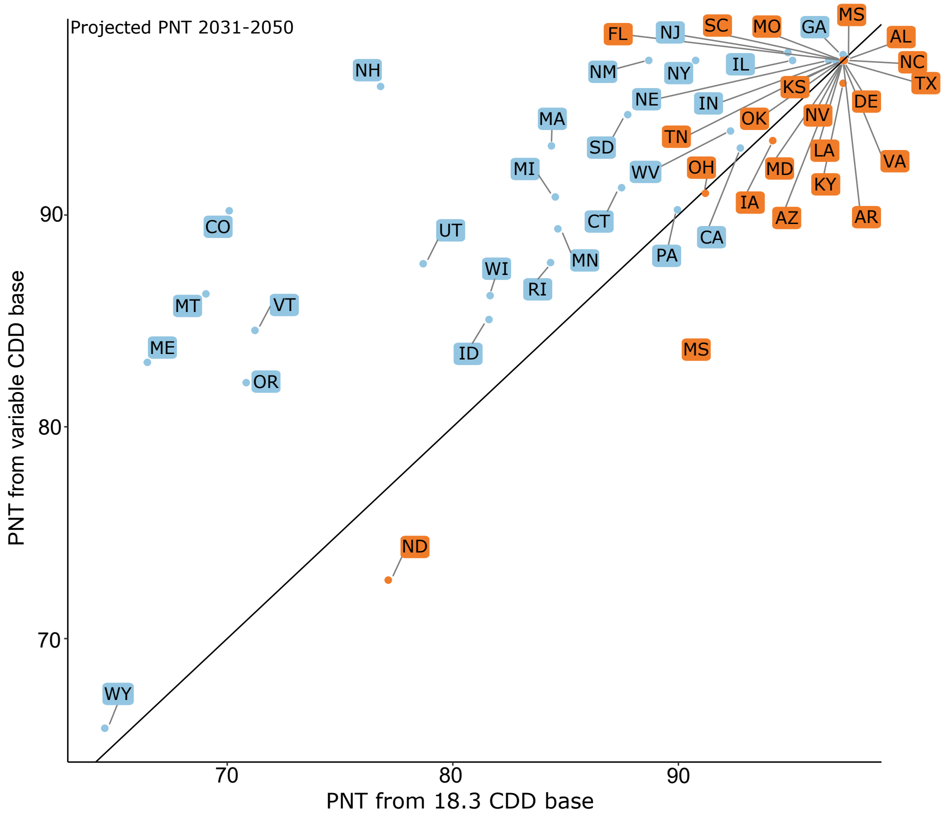

Figure S2. Projected values (2031-2050) PNT from variable CDD versus PNT from the 65°F (18.3°C) base value.

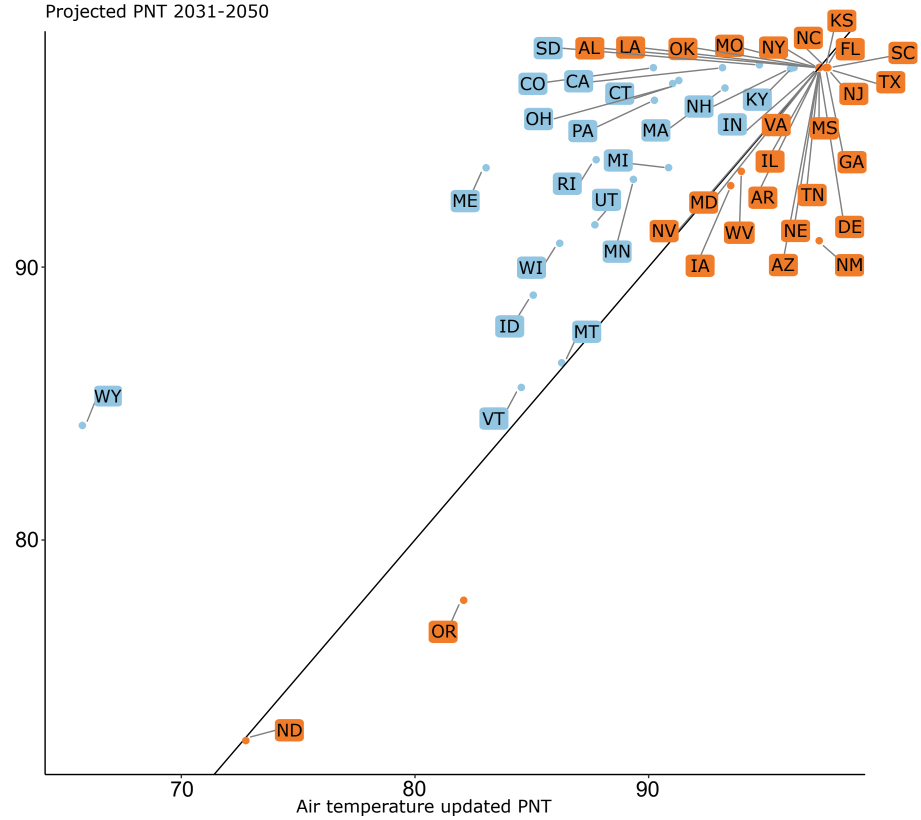

Figure S3. Projected values (2031-2050) PNT from heat index CDD versus PNT from variable CDD.

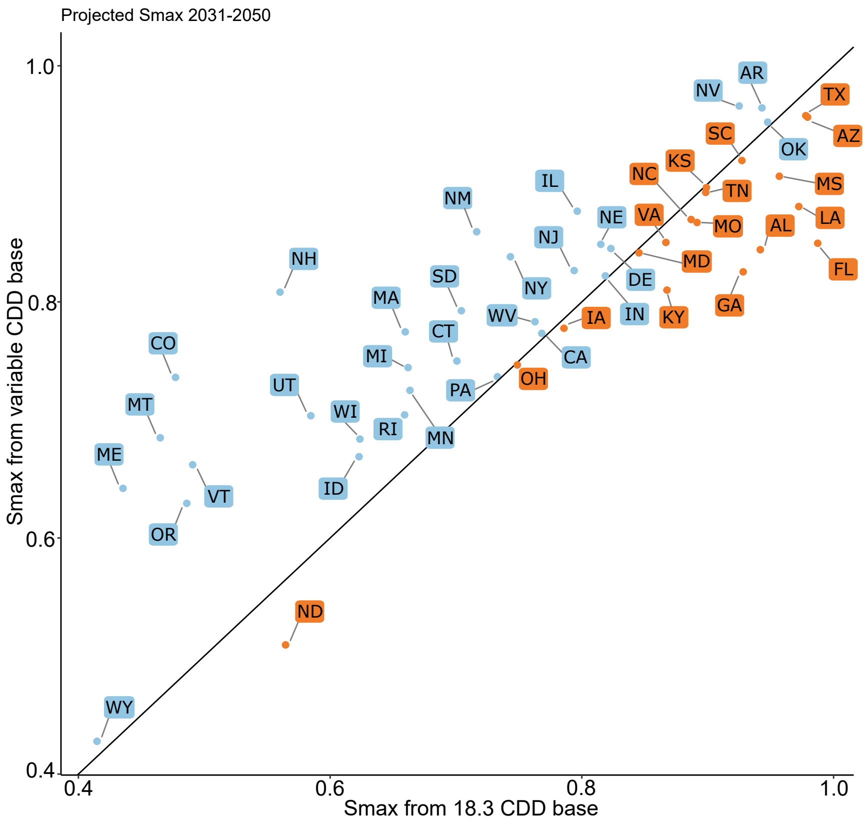

Figure S4. Projected values (2031-2050) Smax from variable CDD versus Smax from the 65°F (18.3°C) base value.

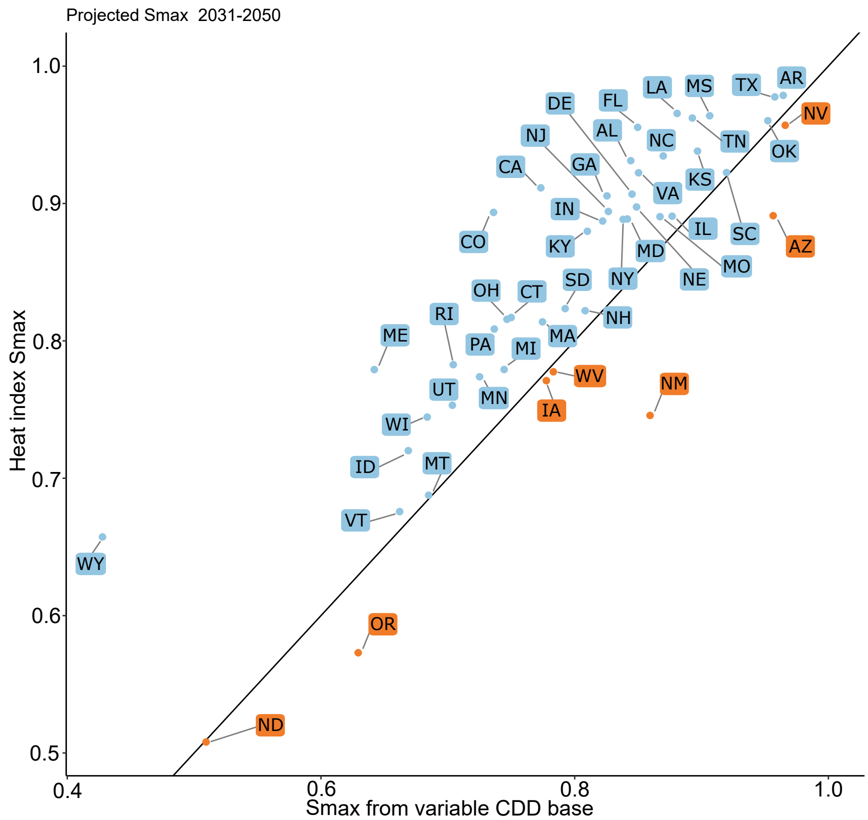

Figure S5. Projected values (2031-2050) Smax from heat index CDD versus Smax from variable CDD.

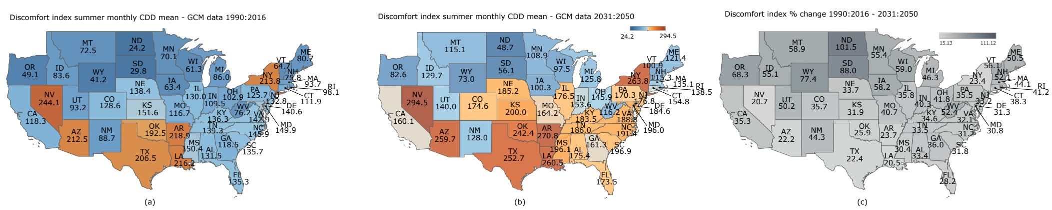

Figure S6. Discomfort index (DI) CDD. (a) represents data from the projected GCMs from 1990-2016 for the summer months (May to September). (b) represents the projected time frame (2031-2050) and summer months, but for the updated discomfort index base. Finally, (c) depicts the difference between the first two panels.