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The hours matter: comparing indicators of US residential cooling from hourly versus daily climate variables

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Abstract

Cooling energy demand in buildings is rapidly increasing as climate warms. Current methods of estimating and predicting residential cooling demand are primarily based on daily temperature, which neglects intraday temperature variations. To determine whether large-scale cooling demand is substantially affected by intraday temperature variations, we conduct a thorough comparison between variable degree days (VDDs) derived from daily temperature data with variable degree hours (VDHs) derived from hourly temperature data during the summer seasons in the United States. The results imply that incorporating intraday variations in temperature will have substantial impacts on cooling estimation and prediction. A comparison of the historical (1990–2014) VDD and VDH calculated from ERA5 temperature data reveals that US summer cooling demand estimated from hourly temperature is 29%–45% higher than those estimated from daily temperature, with differences exceeding 60% when hourly solar radiation is considered. This occurs because the hourly calculations captures the 'hot hours' of the mild days. Future scenario analysis, using the NASA Earth Exchange Global Daily Downscaled Projections, indicates that under the medium greenhouse gas emissions pathway (SSP2-45), US summer VDH and VDD are expected to increase by approximately 45% and 100% by the late century (2081–2100). This suggests that, daily-based predictions generally project cooling demand growth at twice the rate of hourly-based predictions, as the daily method accounts for increases in both high and low temperatures regardless of whether they exceed the baseline, while the hourly method, with its finer temporal resolution, includes only temperatures that surpass the baseline. Such effects are seen across most areas of the US. Our analysis underscores the significance of incorporating temperature data at higher temporal resolution in estimating and predicting cooling demand, which is essential for effectively implementing various measures to achieve energy conservation and climate goals.

1. Introduction

Energy demand for space cooling has become the fastest-growing component of energy consumption in buildings (IEA 2018). This demand is commonly fulfilled with electric fans and air conditioning (AC) systems, and as such, the escalating cooling demand is contributing increasingly to the demand for electricity (Dell *et al* 2014, McFarland *et al* 2015) and resulting in a wide range of impacts. Such impacts include bringing enormous strain on current power systems (Denholm *et al* 2012), generating higher emissions (Abel *et al* 2017, Isaac and van Vuuren 2009, Meier *et al* 2017), and increasing the risk of adverse health impacts associated with poor air quality (Abel *et al* 2018). To manage the rapid growth of cooling demand, actions must be taken on the demand and supply sides (IPCC 2018, Mundaca *et al* 2019). On the demand side, efforts should be made to develop passive solutions for buildings (Bhamare *et al* 2019) and to improve the efficiency of cooling systems, like AC, to curb energy demand growth (IEA 2018, Chen *et al* 2020). On the supply side, a widely discussed measure is the decarbonization of the electricity sector, from generators (IEA 2022) to power systems (Denholm and Hand 2011, Denholm *et al* 2012). Effective implementation of these measures requires a thorough understanding of future cooling demand (Denholm *et al* 2012).

A widely used method for estimating large-scale cooling demand is the cooling degree-day (CDD) measure (CIBSE 2006). The CDD measures the extent to which the daily average temperature exceeds a predefined baseline temperature, which is generally considered the threshold above which cooling is required. Thus, CDD serves as a valuable indicator for evaluating the climate-driven cooling energy demand. This metric has been used to assess the escalating cooling demand globally (Miranda *et al* 2023), as well as in different regions, including North America (Shen 2017, Rastogi *et al* 2019, Chidiac *et al* 2022, Gesangyangji *et al* 2024), Europe (Frank 2005, Olonscheck *et al* 2011, Spinoni *et al* 2018, Janković *et al* 2019, Ramon *et al* 2020) and Asia (Rosa *et al* 2014, Shi *et al* 2021, Ukey and Rai 2021, Muslih 2022).

Where the CDD measure treats each day as an entity and overlooks the intra-day temperature variations, an alternative measure–cooling degree hour (CDH), offers a more comprehensive perspective (CIBSE 2006). The CDH, calculated on hourly temperatures, captures the hourly variation of temperature and, importantly, the daily extreme conditions (Masson-Delmotte *et al* 2013, Vose *et al* 2017). The role of hourly-level cooling demand is frequently acknowledged and explored in empirical studies to investigate the impacts of set point adjustments in individual buildings (De Chalendar *et al* 2023), simulating peak demand and energy savings (Stern and Spencer 2017), and determining the theoretical thermal characteristics of specific building components (Vallejo-Coral *et al* 2019). These studies often focus on testing specific techniques or examining more detailed, micro-level aspects of cooling demand. In contrast, metrics like CDH are more commonly applied in large-scale studies to evaluate broader patterns and trends of climate-driven cooling demand, as demonstrated in research conducted in China (Shi *et al* 2021), Turkey (Oktay *et al* 2011), Italy (Salata *et al* 2022), and European countries (Castaño-Rosa *et al* 2021).

Given the similar applicability of CDH and CDD metrics but their differing temporal resolutions, a thorough comparison between the two would be valuable for understanding and determining whether the building's cooling demand is substantially affected by intraday temperature variations. To date, only a few studies have made the comparison (Cox *et al* 2015, Castaño-Rosa *et al* 2021). Results from (Castaño-Rosa *et al* 2021) demonstrated that CDH outperformed CDD overall in predicting cooling demands in European countries and exhibited a higher sensitivity in detecting smaller changes that CDD failed to capture. Similar findings are reported in an empirical study by the National Renewable Energy Laboratory (NREL), which suggests that hourly-based AC efficiency measures offer greater precision than annual measures in capturing actual energy savings and costs (Stern and Spencer 2017). Cox *et al* also investigated differences in cooling demand estimated from annual and hourly temperatures in Gentofte, Copenhagen, and Denmark (Cox *et al* 2015). They used both the degree-day method and dynamic simulations and found that the differences (between hourly and annual scenarios) can be up to 4%, primarily resulting from some cooling hours being overlooked by the annual scenarios.

To this end, this study aims to enhance our understanding of how intraday temperature variations influence the estimation and projection of cooling demand at a national scale, particularly in large countries like the US, characterized by high cooling consumption. With a focus on the US residential sector, our research unfolds in two distinct phases. We first compare summer cooling demand estimated from daily and hourly temperature and solar radiation for the historical scenario (1991–2015) to study the effects of intraday variations in these climate variables on cooling estimation. Subsequently, we compare changes in the future cooling demand computed from daily and hourly temperatures to investigate the potential influence of temperature change on summer cooling prediction. For the future scenarios, we consider mid- (2041–2060) and late-century (2081–2100), under the medium pathway of future greenhouse gas emissions (shared social-economic pathway, SSP2-45).

Focusing on the climate-driven cooling demand, we use variable degree-days and degree-hours (VDDs and VDHs) (Al-Homoud 2001) as indicators. The VDD and VDH share a similar definition with the CDD and CDH, except that the baseline temperature is arbitrarily fixed for CDD and CDH but is allowed to vary across time and geographic areas in VDD and VDH (see table 2). In fact, using a fixed baseline temperature has been recognized as a primary limitation in CDD metrics, because building heat gains fluctuate over time and across areas (Huang and Gurney 2016). VDD and VDH approaches effectively address that limitation, and therefore, hold the potential to yield a more realistic estimation of cooling demand.

The methodology for calculating VDD draws from the Cooling and Heating Global Energy Demand model (CHILLD), developed by the International Institute for Applied Systems Analysis (IIASA) (Mastrucci *et al* 2021). Nonetheless, Mastrucci *et al* did not introduce VDH in their study, so we downscaled the VDD calculation to VDH calculation by converting the daily climate variables, including temperature and solar radiation, into an hourly scale. Unlike the daily-scale temperatures that can be sourced directly from climate models (Semenov and Stratonovitch 2010) and used for VDD calculation, the granular hourly data required for VDH calculations demands additional computational efforts, like statistical downscaling of monthly or daily temperature to an hourly scale (Belcher *et al* 2005, Oktay *et al* 2011, Gesangyangji *et al* 2022). Alternatively, depending on the specific research question, local climate variables can be dynamically simulated at fine temporal and spatial resolution using regional climate models (Shi *et al* 2021, Salata *et al* 2022). For example, sub-daily climate projections that thoroughly incorporate the impacts of the urban environment were developed by (Georgescu *et al* 2018) and have been applied in relevant studies in the US (Krayenhoff *et al* 2018). Additionally, open-source tools, like the R package *Helios* (Zhao *et al* 2024) and Python package *tell* (McGrath *et al* 2022), which align with the Global Change Analysis Model for the United States are available for modeling the impacts of climate change on energy demand, but with some limitations: *Helios* calculates degree-hours on a fixed balance temperature, and *tell* supports analysis at the state level. In this study, we developed a recalling method to produce future hourly temperatures from historical observations and future daily projections. This method builds upon and optimizes our previous approach (Gesangyangji *et al* 2022). Detailed explanations are provided in the subsequent section. By using globally accessible datasets, our method opens the door to applying the rescaling technique worldwide, thereby addressing the ongoing challenges associated with generating high temporal-resolution temperature projections.

2. Data and methods

2.1. Overview: calculation of VDD and VDH

The calculation of VDD and VDH is based on the approach used in the CHILLD model developed by IIASA. The model follows three steps to calculate large-scale residential energy demand: (1) calculating baseline temperature that incorporates heat gains from various heat sources, such as internal heat gains and solar radiation, as well as generalized building thermal characteristics that affect solar heat gains; (2) calculating variables degree days which is the key climate indicator used to estimate climate-driven cooling demand; (3) calculating final energy demand by involving other drivers, like population, housing characteristics, and cooling systems.

Computation of VDD and VDH is based on the first two steps of the CHILLD model, as illustrated by equations (1) and (2). It starts with determining the baseline temperature T_{bal} (°C) from the indoor set-point temperature T_{sp} (°C), heat gain from solar heat sources g_{sol} (W) and internal heat sources g_{int} (W), and heat transfer coefficient by transmission H_{tr} and ventilation H_{ve} (W °C^{-1}). Subsequently, the baseline temperature and outdoor temperature T_{out} (°C) are used to compute VDD and VDH (°C) for a given time,

$$T_{\text{bal}} = T_{\text{sp}} - \frac{g_{\text{sol}} + g_{\text{int}}}{H_{\text{tr}} + H_{\text{ve}}} \tag{1}$$

$$\text{VDD or VDH} = \sum_{t=1}^{N} \left(T_{\text{out}} - T_{\text{bal}}\right)^{+}. \tag{2}$$

Our study, delving into the effects of intraday fluctuations in climate variables, focuses on two key factors: g_{sol} and T_{out}. Daily mean solar radiation and temperature are used for the calculation of VDD, while hourly solar radiation and temperature are used for VDH. The relevant climate datasets and methodologies are presented in the subsequent sections. The non-climate variables used in the equations (1) and (2) are listed in table 1. These values were retained as originally provided in the CHILLD model because they have proven applicability and are not the primary focus of this study. For a detailed exploration of the variables in the CHILLD model and their origins, we refer readers to (Mastrucci *et al* 2021) for further insights.

2.2. Solar radiation

To calculate heat gain from solar heat source g_{sol} (W), hourly mean surface downward short-wave radiation flux (GHI, also known as global horizontal irradiance, W m^{-2}) and hourly mean surface direct short-wave radiation flux (DIR_H, W m^{-2}) were derived for1991 to 2015 from the ERA5 dataset (Hersbach *et al* 2023). Figure 1 depicts the solar data processing workflow. GHI and DIR_H are processed using the Python package 'pvlib' (Holmgren *et al* 2018) and the decomposition method introduced by (Zhang *et al* 2021) to calculate direct (DIR) and diffuse (DIF) components of solar radiation on horizontal (H) and vertical (V) surfaces. Direct components on a vertical surface were computed at different orientations (east, north, south, and west) to consider the variation in solar gain caused by the changing position of the sun (Wang and Xu 2006), and then averaged to determine

Table 1. Non-climate variables.

T_{sp} (°C)	g_{int} (W)	H_{tr} (W °C^{-1})		H_{ve} (W °C^{-1})
		Closed window	Open window	
26	2.14	0.5	1.5	2.1128

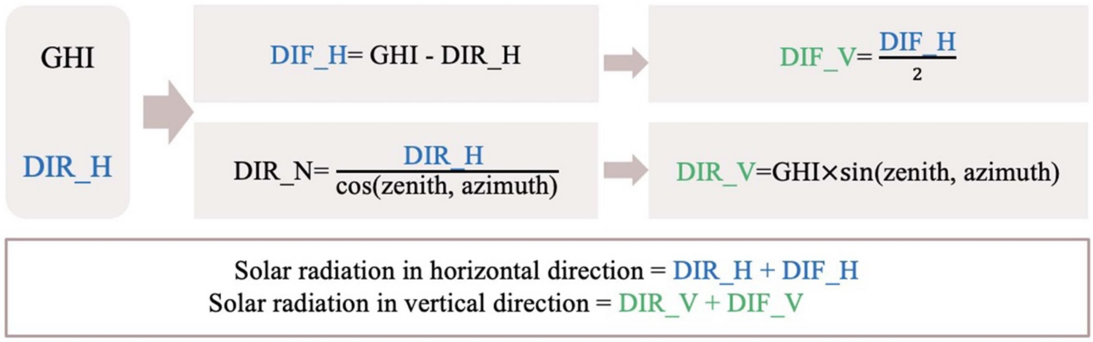


Figure 1. Solar data processing workflow. Components are categorized by direction: blue for horizontal (_H) and green for vertical (_V). GHI represents hourly global horizontal irradiance; DIR_N is direct normal irradiance. DIR_H, DIF_H, DIR_V, and DIF_V are the direct (DIR) and diffuse (DIF) components of solar radiation on horizontal (_H) and vertical (_V) surfaces, respectively.

the overall direct components. The diffuse components were considered isotropic, so the flux incident on a vertical surface is considered half of the flux incident on a horizontal surface.

The ERA5 data were provided on a spatial resolution of 0.25° × 0.25° and were aggregated to 0.5° × 0.5° to ensure consistency with spatial resolution of CHILLD. The process in figure 1 was applied to each grid cell and for each hour of the period spanning from 1991 to 2015. The results were then averaged over the days and years to determine the hourly pattern of total radiation in horizontal and vertical directions for June, July, and August, and used for calculating heat gain from transparent elements like windows and the opaque surface like roofs. The calculation of heat gains follows the methods outlined by (Mastrucci *et al* 2019), with the detailed formula and explanation provided in the section 1 of supplementary materials.

2.3. Temperature

While historical temperature data is readily available from various sources at both hourly and daily scales, future temperature projections are typically provided only on a daily scale. To address this, we generated future hourly temperature data using a rescaling method, as detailed in the following sections. This method represents an enhancement of our previous approach (Gesangyangji *et al* 2022). Whereas the earlier method was limited to the eastern US due to data availability constraints, the improved version utilizes globally available datasets, allowing it to be applied across the contiguous US and other regions worldwide.

(1) *Data*

For the historical scenario, we used hourly temperature data from the ERA5 dataset (Hersbach *et al* 2023) spanning from 1991 to 2015. For future scenarios, we obtained projected T_{max} and T_{min} from the NASA Earth Exchange Global Daily Downscaled Projects (NEX-GDDP-CMIP6) (Thrasher *et al* 2012, 2022) for mid- (2041–2060) and late-century (2081–2100), under the RCP4.5. Both ERA5 and NEX-GDDP data provided on a spatial resolution of 0.25° × 0.25° were aggregated to 0.5° × 0.5° to ensure consistency with spatial resolution of CHILLD.

NEX-GDDP provides downscaled products from over 30 global climate models (GCMs), which were debiased on observations using the bias correction spatial disaggregation method (Thrasher *et al* 2012). We selected nine GCMs that were found to demonstrate the highest fidelity in simulating the present climate in North America (Almazroui *et al* 2021), and then narrowed them down to five based on our focused research period and scenarios (some models do not have complete data for selected scenarios and years). The five models used are GFDL-ESM4, ACCESS-CM2, MPI-ESM1-2-HR, EC-Earth3, and NorESM2-MM. In this analysis, VDD and VDH were calculated for each of the five models to preserve the potential variations between models and then were averaged to yield a mean value. Hourly and spatial patterns of the VDH from the five selected models were compared and found to have good consistency (supplementary material, section 2).

(2) *Rescaling method*

The updated rescaling method is presented in figure 2. It uses ERA5 hourly temperatures and T_{max} and T_{min}

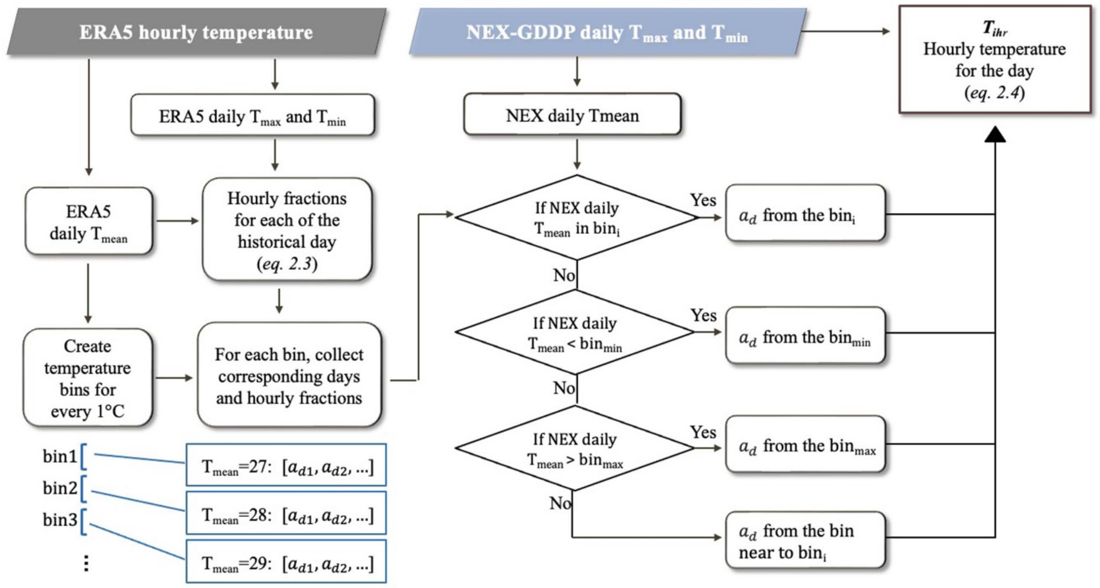


Figure 2. Schematic diagram of the method used to produce future hourly temperatures. This process was implemented on every single grid cell and every single hour of the selected period.

to compute the fractional diurnal ranges (a_{ihour}) for days of the historical period (equation (3)). These fractional relationships are then applied to projected T_{max} and T_{min} to produce future hourly temperature profiles (equation (4)),

$$a_{ihour} = \left(T_{ihour} - \mathrm{Tmin}_{iday}\right) / \left(\mathrm{Tmax}_{iday} - \mathrm{Tmin}_{iday}\right) \tag{3}$$

$$T_{ihour} = a_{ihour} \times \mathrm{Tmax}_{iday} + (1 - a_{ihour}) \times \mathrm{Tmin}_{iday}. \tag{4}$$

The first step produces fractional diurnal ranges (a_{ihour}) from ERA5 data, for every single hour during 1991–2015 per grid cell. Concurrently, temperature bins were created for every 1 °C based on historical daily mean temperature (T_{mean}) per grid cell. Then, for each temperature bin, corresponding days and fractional diurnal ranges (a_d) were identified and saved for later use. Please note that while a_{ihour} represents the fraction for a single hour, a_d in figure 2 refers to the pattern of fractional diurnal ranges for the day. To ensure that each temperature bin was representative, bins with less than ten days were merged with their nearest bin. This approach helped to reduce the impact of abnormal extreme conditions. For instance, if the number of days where the historical T_{mean} exceeded 35 °C in a specific location was less than 10 d during 1991–2015, then the bin for 35 °C would be merged with the bin for 34 °C.

Thereafter, future T_{mean} was calculated from the T_{max} and T_{min} of NEX-GDDP data and was used to determine the corresponding temperature bin. In this stage, we considered four possible scenarios for a future day: (1) if the future T_{mean} corresponds to a temperature bin, we randomly select an a_d from the current bin. (2) if the value of future T_{mean} exceeds the upper boundary of the maximum bin which is expected in the context of global warming, we randomly select an a_d from the maximum bin. (3) if the value of future T_{mean} falls below the lower boundary of the minimum bin, we randomly select an a_d from the minimum bin. (4) If none of the aforementioned conditions are met, indicating that the specific value of future T_{mean} has never occurred in the historical scenario, in this case, we randomly select an a_d from the bin that is closest to the value of future T_{mean}. Finally, the hourly temperature for a future day was calculated through equation (4) using the T_{max} and T_{min} and the corresponding fractional diurnal ranges. This rescaling process was performed on each grid cell for the entire US and for every single hour of the historical and future scenarios to produce the hourly temperature.

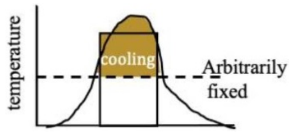
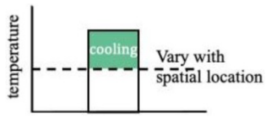
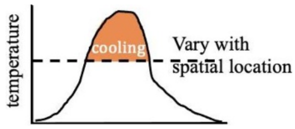
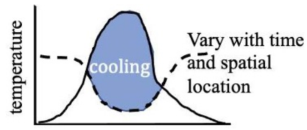
Finally, aforementioned processes provide hourly heat gains and future hourly temperatures for every single hour in each period and for each grid cell over the US. These data were used to compute the gridded VDH, which was then aggregated over the US for selected period to represent US cooling demand of the period. The calculation of VDD was based on the same data sources, except that the data is on the daily scale.

3. Results

3.1. Impacts of intraday variations of climate variables on cooling estimation

To investigate the effect of intraday variations of solar radiation and temperature, we compared historical daily cumulative cooling estimation over the US under three cases (Case 1, 2, and 3 in table 2). We also

Table 2. Characteristics of methods used for estimating daily cooling demand.

	Variable name	Method	Climate variables: Solar radiation	Climate variables: Temperature	Graphic illustration *Solid lines: outdoor temperature* *Dashed line: baseline temperature*
Case 0	CDD/CDH	Cooling degree days and hours	Not included	Daily/hourly	
Case 1	VDD	Variable degree days	Daily	Daily	
Case 2	MVDH1	Mean variable degree-hours	Daily	Hourly	
Case 3	MVDH2	Mean variable degree-hours	Hourly	Hourly	

show a Case 0 to differentiate the CDD and VDD metrics. Case 0 accounts for temporal and spatial variation of outdoor temperature, while the variation of solar radiation is not incorporated on either spatial or temporal scales. In Cases 1–3, spatial variations of solar radiation are considered, with distinctions in how temporal variation of the two variables are incorporated. Case 1 considers solar radiation and temperature on a daily scale and thus neglects their intraday variations. Case 2, using daily solar radiation and hourly temperature, only takes into account the intraday variations of temperature while assuming homogenous effects of solar radiation for a given day. Case 3 uses hourly temperature and hourly solar radiation to include variations of both variables throughout the day. The three cases are calculated on VDD and VDH methods. Since the VDD is given on a daily scale while the VDH is on an hourly scale, VDHs of the day were averaged to compute an MVDH (mean VDHs of the day) to represent the daily estimation. Consequently, the Case 1, Case 2, and Case 3 are represented by VDD, MVDH1, and MVDH2, respectively, as illustrated in table 2.

3.1.1. Impacts of intraday variations of temperature

The cumulative daily cooling estimates for the US during the summer months from 1991 to 2015 are presented in figure 3. Comparisons between the VDD (green bar) and MVDH1 (orange bar) highlight the effects of intraday variations of temperature. Specifically, the differences from the daily-scale estimation (VDD) and hourly-scale estimation (MVDH1) demonstrate that MVDH1 exceeds VDD by 53%, 35%, and 38% in June, July, and August, respectively. These figures suggest that using hourly temperature data results in higher climate-driven cooling estimation compared to daily temperature data. Similar findings regarding the higher sensitivity of hourly metrics have also been observed in European countries. (Cox *et al* 2015, Castaño-Rosa *et al* 2021).

While a positive effect is shown across most areas of the US, it is most prominent in the western regions (see figure 4's second column). These western regions typically have lower mean temperatures and significant diurnal variations. Consequently, as shown in figure 4's first column, VDD tends to be zero as the daily mean temperature is lower than the baseline temperature. Conversely, MVDH1 can be above zero as it takes into account the hot hours where the temperature exceeds the baseline temperature. As an illustrative example, we consider Garfield County, Colorado, which is displayed in figure 7 and will be discussed in section 2.

On the other hand, the hourly temperature has a minimal impact on cooling estimates in southern regions. This is because these areas often have higher temperatures with smaller diurnal variations, and as such, both daily mean and hourly temperatures are above the baseline temperature. Thus, daily cooling requirements estimated from daily mean temperature and from averaged hourly cooling needs are the same. Orlando, Florida exemplifies this situation (figure 7).

However, interestingly, slight negative effects are seen in southern coastal areas like Florida, where using daily temperature leads to higher cooling estimation. This can be attributed to the typical method of calculating daily mean temperature. Specifically, VDD uses the daily mean temperature calculated by averaging the daily T_{max} and T_{min}, while the MVDH1

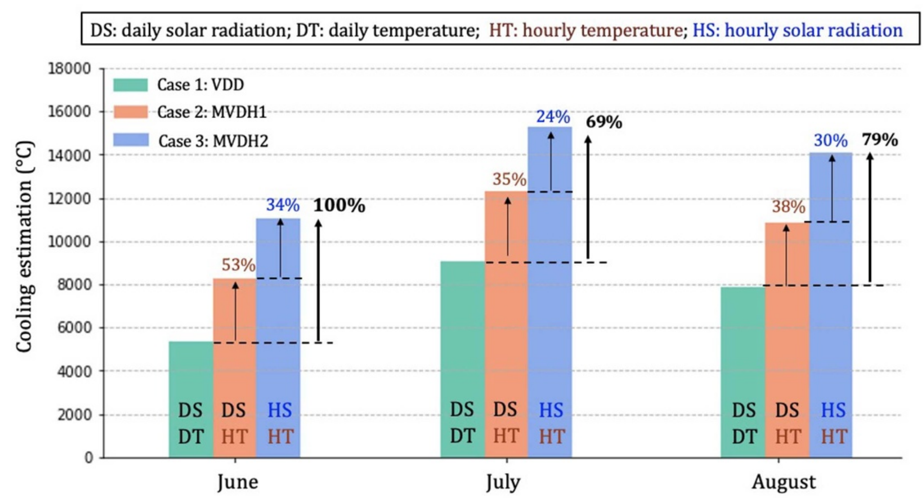


Figure 3. Daily cumulative cooling demand over the US estimated for summer months during 1991–2015. The three bars correspond to the three cases. Green: Case 1, variable degree days (VDD); Orange: Case 2, mean variable degree-hours with daily solar radiation considered (MVDH1); Blue: mean variable degree-hours with hourly solar radiation considered (MVDH2).

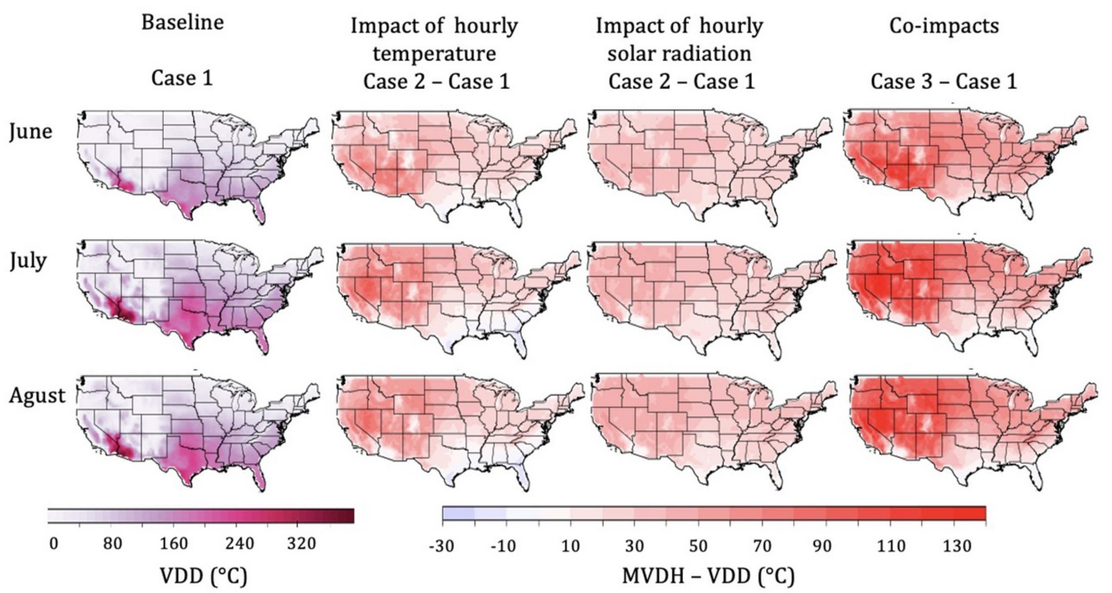


Figure 4. Differences in daily cooling demand estimated from different approaches. The first column presents the baseline case of summer cooling estimation calculated on VDD (Case 1, green bars in figure 1). The second column shows the effects of hourly temperature (MVDH1—VDD, differences in orange bars and green bars in figure 1). The third column indicates the effects of hourly solar radiation (MVDH2—MVDH3, differences in blue bars and orange bars in figure 3). The fourth column is the co-effect of hourly solar radiation and hourly temperature (MVDH2—VDD, differences in blue bars and green bars in figure 1).

approach computes daily values yielded from averaging all hourly temperatures of the day. For example, in Miami, Florida, the average of the daily $T_{\max}$ and $T_{\min}$ on a sample summer day is 28.6 °C, whereas the average hourly temperature for the day is 27.6 °C. This discrepancy raises questions about the representativeness of the mean daily temperature obtained from $T_{\max}$ and $T_{\min}$ and highlights the importance of incorporating hourly variation for a more representative mean condition and a precise cooling estimation.

3.1.2. Impacts of intraday variations of solar radiation

The effect of intraday variation of solar radiation is presented by differences between MVDH1 (orange bar) and MVD2 (blue bar) in figure 3. Compared to the case where daily solar radiation is used, using hourly solar radiation leads to a 24%–34% higher cooling estimation. The overall effects are moderately less than the effects of hourly temperature.

Spatially (see the third column of figure 4), the positive effect is seen across the US, and the effects are relatively more pronounced in the West. This phe-

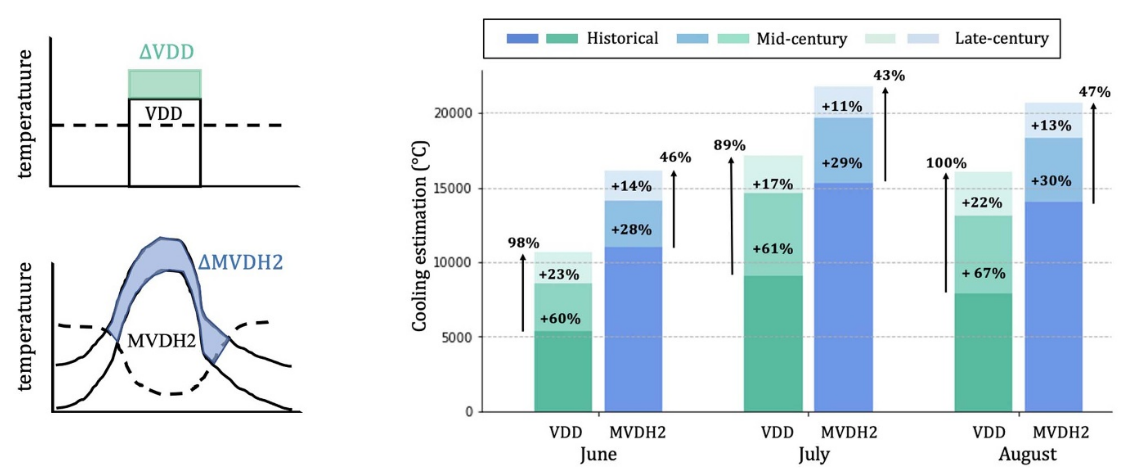


Figure 5. Left: graphic illustration of the future cooling changes predicted from the daily temperature changes (top) and hourly temperature change (bottom). Right: future changes in the U.SS. cumulative VDD (green) and MVDH2 (blue), by mid-century and late-century. The bottom bars are the historical values; the middle bars are the increase by mid-century; and the top bars are the increase by late-century (relative to mid-century).

nomenon can be linked to the distribution of heat gain from the solar heat source, particularly from vertical solar radiation through transparent surfaces like windows. The effect of solar radiation is considered through the heat gain from the solar heat source and is considered on the horizontal and vertical direction (discussed in method section). Although horizontal solar radiation shows a larger magnitude than vertical solar radiation, heat gain from the vertical direction is typically greater, because it passes through transparent surfaces like windows, which have higher thermal transmittance. In contrast, horizontal solar radiation usually hits opaque surfaces like roofs, resulting in less heat gain. Hourly distribution of solar radiation and corresponding heat gains are provided in supplementary material (figure S.2).

3.1.3. Co-impacts of intraday variations of temperature and solar radiation

The graphic illustration in table 2 (see Case 3) shows that the effect of hourly solar radiation and hourly temperature jointly peak during the daytime. As a result, summer cooling demand estimated on hourly solar radiation and hourly temperature is substantially higher than that estimated from daily values. MVDH2 of summer months are all over 69% higher than VDD, and the number is even doubled in June.

Comparing the first and the fourth columns of figure 2 shows that impacts of intraday variation of the two climate variables are more pronounced in areas with lower VDD, and vice versa. This suggests that using daily climate conditions is likely to underestimate cooling demand in large parts of the US, especially in areas with colder mean climate conditions, such as the Rocky Mountain area. In warmer places like south Texas and Florida, intraday variation of temperature and solar radiation shows negligible impact on cooling estimation.

3.2. Impacts of future temperature change on cooling demand prediction

Temperature is known to be the primary climate driver influencing future changes in large-scale cooling demand (Rastogi *et al* 2019). Future daily temperature projections are typically obtained by calculating the mean of projected $T_{\max}$ and $T_{\min}$ given by GCMs. This means that predicting cooling demand from the projected daily temperature uniformly incorporates changes in $T_{\max}$ and $T_{\min}$. However, as illustrated in the left panel of figure 5, despite the rapid increase in $T_{\min}$ or in nighttime temperatures, its impact on the cooling demand remains a matter of inquiry. This uncertainty arises because the new minimum temperature in certain locations may remain below the defined baseline temperature threshold for cooling demand, suggesting no significant increase in cooling requirements even under future warming scenarios. For instance, if the baseline cooling threshold temperature in Madison, Wisconsin, is 23 °C, future nighttime temperatures in summer—though predicted to rise significantly from 15 °C to 16 °C—would remain below this threshold. Consequently, no additional nighttime cooling demand would be anticipated in this scenario, despite the observed warming trend.

In this section, we compare the future changes in VDD and MVDH2, denoted as ΔVDD and Δ MVDH2, to investigate the potential influence of future temperature change on cooling demand prediction. Please note that the impact of future changes in solar radiation is beyond the scope of this study, so ΔMVDH1 is excluded in this section. To ensure ΔVDD and Δ MVDH2 are led by temperature

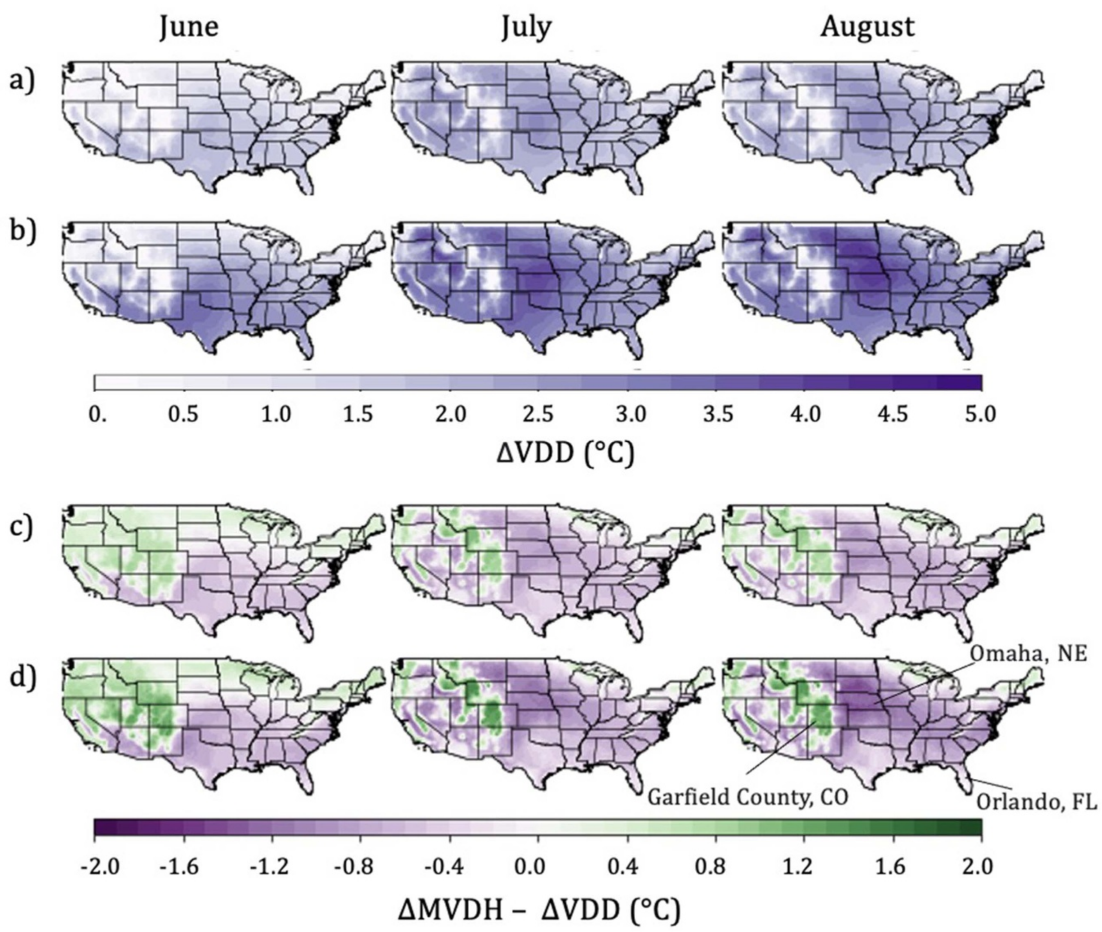


Figure 6. Spatial distribution of ΔVDD and differences between ΔVDD and ΔMVDH2. Panels (a) and (c) correspond to the mid-century and panels (b) and (d) correspond to the late-century. In panels (c) and (d), positive values indicate a larger Δ MVDH2 compared to ΔVDD, suggesting that using MVDH2 leads to a faster rate of increase, while negative values suggest the opposite effect.

changes, historical solar radiation was used for historical and future scenarios.

As climate warms, VDD and MVDH2 is projected to increase throughout the 21st century (see right panel of figure 5), with a larger increase in the first half of the 21st century. The rise in cumulative VDD by the mid-century, ranging from 60% to 67%, are noticeably greater than the increase in MVDH2, which are around 29% in all months. During the latter half of the 21st century, the percentage increase of cooling demand from both methods are under 23%, with ΔMVDH2 remain lower than ΔVDD.

Spatial distribution of ΔVDD and differences between ΔVDD and ΔMVDH2 is presented in figure 6. The top two panels, indicating positive ΔVDD across the US, suggest an increased summer cooling demand in this country, with the most increases in the Midwest, and the least increases in the Rocky Mountain area. This spatial trend align well with the summer CDD changes indicated by (Rastogi *et al* 2019). When comparing ΔVDD and ΔMVDH2 (as shown in panels (c) and (d)) of figure 6), we observe three distinct cases: ΔVDD being either equal to, larger than, or smaller than ΔMVDH2, but the spatial pattern and magnitude of these differences vary by months. In June, a slightly higher ΔVDD (purple) is observed in the southern half of the US, while a higher ΔMVDH2 (green) is shown in the West, upper Midwest, and the Northeast region. In July and August, the higher ΔVDD pattern extends northward and is seen in most areas of the country, except for the Rocky Mountain region, where it shows an even higher ΔMVDH2 instead (as green gets darker). Although the Midwest region, especially South Dakota and Nebraska see minimal differences in June, these areas show the largest difference in July and August. During these 2 months, the least differences are seen in some southern areas such as Texas and Florida, and some northeast areas.

To gain insight into the factors contributing to the differences in ΔVDD and ΔMVDH2, we select three locations (as marked in figure 6) and investigate their temperature pattern in August (figure 7). Omaha, Nebraska exemplifies the regions with higher ΔVDD values, Garfield County in Colorado represents areas with higher ΔMVDH2 values, and Orlando, Florida serves as an indicator of regions where ΔVDD and ΔMVDH2 values are roughly equal.

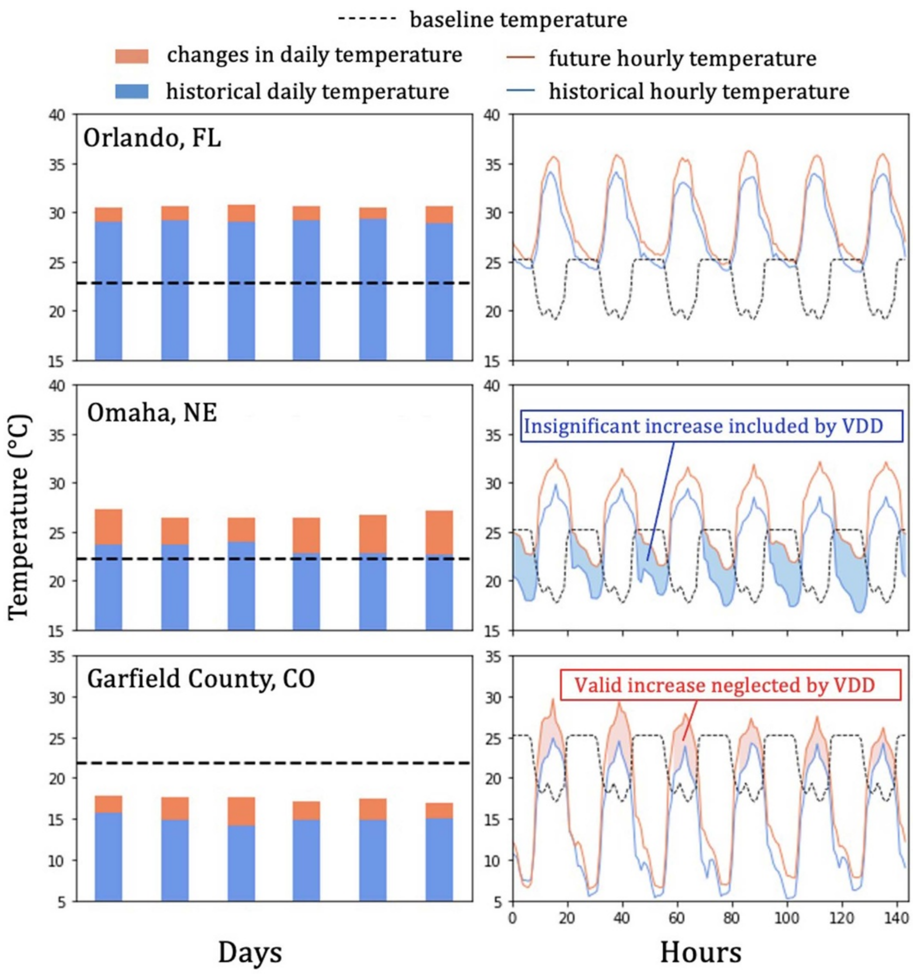


Figure 7. Daily and hourly temperature patterns for three selected locations and six random days in August. Changes in daily temperatures and future hourly temperatures are referred to as the late-century scenario. Temperatures here are derived from a single model, NorESM2-MM.

Results show that differences in ΔVDD and ΔMVDH2 can be attributed to the 'valid increase' in hourly temperature. The 'valid increase' here refers to the temperature rise that contributes to the cooling demand by exceeding the baseline temperature. Conversely, we use 'insignificant increase' to describe the temperature rise that has no impact on cooling demand.

In the case of Orlando, historical daily and hourly temperatures are already consistently above the corresponding baseline temperature, so any future rise in temperatures will contribute to the increase of cooling. Thus, ΔVDD and ΔMVDH2 are about the same. In Omaha, substantial temperature increases are projected during both warmer hours (i.e. daytime and $T_{\max}$) and colder hours (i.e. nighttime and $T_{\min}$). When calculating the increase in daily temperature, rises in both $T_{\max}$ and $T_{\min}$ are included, resulting in increasing VDD that reflects the warming at both ends of the spectrum, regardless of baseline temperature. However, in the calculation of ΔMVDH2, the rise in colder temperatures (as marked in figure 7) is deemed insignificant because the future temperature remains under the baseline temperature, rendering it inconsequential for cooling requirements. Consequently, the increase in VDD is higher than that in MVDH2. The opposite is true in the case of Garfield County. Due to the relatively lower mean temperature and high diurnal variations, cooling demand is not recognized on a daily basis. However, hot hours where the temperature reaching 30 °C highlight the necessity of cooling in this location. In the future, despite the increases, the daily mean temperature will remain below the baseline temperature, resulting in no changes to VDD. However, increases in the warm temperatures (as marked in figure 7) will lead to growing cooling demand, which is reflected by higher ΔMVDH2 in figure 6.

The disparities between ΔVDD and ΔMVDH2, along with their spatial fluctuations, underscore the importance and necessity of incorporating temperature changes on a higher temporal scale when predicting cooling demand. Failing to consider warming on hourly scale may lead to either an underestimation or an overestimation of future cooling demand and may further affect local and regional energy planning and management.

4. Discussion

4.1. Main findings

This study aims to evaluate the impact of intraday temperature variations on cooling estimation and projection in the US residential sector. It begins by comparing two cooling metrics—VDDs and VDHs—across the US during the summer months of the historical period (1990–2014) to assess how cooling demand calculated from daily temperature data compares to that calculated from hourly temperature data. Then, the projected changes in VDD and VDH for mid-century and late-century under the SSP245 scenario are compared to explore the impacts of temporal resolution of temperature data on future cooling predictions.

The results suggest that incorporating intraday temperature will result in higher cumulative cooling demand in the US. Specifically, VDH-based daily cumulative cooling estimate is 29%–45% higher than VDD, and when combined with hourly solar radiation, the increase can exceed 60%. These impacts are particularly pronounced in the West. Our findings, showing higher cooling metrics from VDH compared to VDD, align with EU-focused studies (Cox *et al* 2015, Castaño-Rosa *et al* 2021). These studies demonstrate that hourly-scale metrics can detect hot hours that are often smoothed out in daily mean conditions, resulting in higher cooling demand estimates. The importance of hourly-scale estimation is further supported by an empirical study from NREL which shows that hourly-based AC efficiency measures provide greater precision than coarser temporal measures in capturing actual energy savings and costs (Stern and Spencer 2017).

Both VDD and VDH metrics indicate a rapid increase in summer cooling demand throughout the 21st century, with the most increase in the Midwest, as noted by (Rastogi *et al* 2019). However, the VDD metric shows greater increases across most of the US compared to the VDH metric. Exceptions occur in the Rocky Mountain area, where the results are reversed, and in some southern areas, where both metrics show similar changes. In the case where VDD increases more rapidly than VDH, the additional increases in VDD result from the inclusion of insignificant temperature rises—those that increase but remain below the baseline temperature and, therefore, do not contribute to cooling—in the calculations. In the Rocky Mountain area, VDD metrics can overlook substantial increases in T_{max} by averaging with low T_{min} values, and leading to an underestimation of cooling needs. These differences further emphasize the importance of incorporating temperature projections with high temporal resolution in cooling predictions.

4.2. Sensitivity analysis

This study assumes that the indoor temperature in the US is consistently maintained at 26 °C, a value retained from the original CHILLD model and also close to the optimal set point recommended by the US. Department of Energy (78°F or 25.6 °C) []. Given the high sensitivity of cooling demand to set point (Byers *et al* 2024), we included a sensitivity analysis in the supplementary material (section 4) to examine how VDD and VDH respond to changes in set point. Increasing the set point from 22 °C to 26 °C leads to a decrease in both VDD and VDH, with VDD dropping more sharply, resulting in a larger difference between the two metrics. In other words, our results represent an upper bound for the difference between VDD and VDH. However, regardless of the setpoint temperature (the threshold), the VDH metric consistently estimates higher cooling demand than VDD, underscoring the effects of the temporal resolution of temperature data in cooling demand estimation.

4.3. Limitations and avenues for further research

This study primarily focuses on temperature-driven cooling demand. In reality, cooling demand is influenced by a wide range of factors, including other climate variables, such as humidity (Maia-Silva *et al* 2020) and solar radiation (Li *et al* 2020), as well as non-climate factors like population, behavior, and building characteristics (Berrill *et al* 2021, Mastrucci *et al* 2021). Here, we emphasize the effects of temperature projection, the dominant driver in large-scale cooling demand (Suckling and Stackhouse 1983, Zhai and Helman 2019), but the impact of solar radiation and humidity should be considered in future works. Additionally, while generalized building thermal characteristics were included in calculating baseline temperatures, these were not treated as direct drivers of cooling demand. A more realistic cooling demand model should incorporate detailed building attributes, such as housing size, cooling system efficiency, operational hours, and other parameters. Furthermore, the impact of urbanization should be considered, given its essential effects on climate warming (e.g. urban heat island effects) (Georgescu *et al* 2014), diurnal temperature variation (Krayenhoff *et al* 2018), and cooling system usage (e.g. increased building footprint and higher accessibility and usage of AC). For more realistic cooling demand predictions in the US, future studies should incorporate these factors at a finer spatial resolution, utilizing high-resolution climate projections, such as those produced by (Georgescu *et al* 2014).

5. Conclusion

A reliable prediction of cooling demand is crucial for implementing effective measures on both the demand and supply sides to achieve energy conservation and climate goals. This study highlights the importance of incorporating high temporal resolution temperature data into large-scale cooling demand estimation and prediction. Our findings indicate that, in the US, residential cooling demand estimates based on hourly temperature data are significantly higher than those based on daily temperature data, however, the growth rate of cooling demand based on hourly temperature data is generally slower than that calculated from daily temperature data.

Cooling demand is a complex process influenced by numerous factors. While other drivers may contribute to variations in cooling estimation, our study highlights that temporal resolution is a critical perspective for improving current cooling demand models and achieving more accurate predictions. Moreover, our methodology for generating high-resolution temperature data and improving cooling demand predictions is based on global datasets, making it applicable worldwide and providing a valuable framework for advancing effective energy and climate planning across diverse regions.

Data availability statement

All data that support the findings of this study are included within the article (and any supplementary files).

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Conflict of interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence.

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