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A methodology for evaluating the effects of climate change on climatic design conditions for buildings and application to a case study in Madison, Wisconsin

Gesangyangji1,∗, Daniel J Vimon1,2, Tracey Holloway1,2 and David J Lorenz2,3

1 Nelson Institute Center for Sustainability and the Global Environment, University of Wisconsin-Madison, Madison, Wisconsin 53705, US
2 Department of Atmospheric and Oceanic Sciences, University of Wisconsin-Madison, Madison, Wisconsin 53705, US
3 Nelson Institute Center for Climatic Research, University of Wisconsin-Madison, Madison, Wisconsin 53705, US

∗ Author to whom any correspondence should be addressed.
E-mail: gesangyangji@wisc.edu

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Abstract

Climatic design conditions are widely used by the building community as environmental parameters informing the size and energy requirements for heating, ventilation and air conditioning systems, along with other building design characteristics. Climatic design conditions are calculated by the American Society of Heating, Refrigerating and Air-conditioning Engineers using historical climate data. Our work advances methods for projecting future climate design conditions based on data from global climate models. These models do not typically archive the hourly data required for climate design condition calculations, and they often exhibit large biases in extreme conditions, daily minimum temperatures and daily maximum temperatures needed for climatic design conditions. We present a method for rescaling historical hourly data under future climatic states to estimate the impact of climate change on future building climatic design conditions. This rescaling method is then used to calculate future climatic design conditions in Madison, Wisconsin, throughout the 21st century for two future greenhouse gas emissions scenarios. The results are consistent with a warming climate and show increases in heating, cooling, humidification and dehumidification design conditions, suggesting less extreme cold conditions and more extreme hot and humid conditions in Madison. The design conditions used for estimating energy demand, degree days, show that under a business-as-usual scenario, by the mid-century, building heating and cooling in Madison (climate zone 5A) will be similar to the current heating demand in Chicago, IL (climate zone 5A) and cooling demand in Baltimore, MD (climate zone 4A); by the late-century, building heating and cooling in Madison will resemble the current heating demand in St Louis, MO (climate zone 4A) and cooling demand in Augusta, GA (climate zone 3A). Given the rapid pace of climate change in the 21st century, our work suggests that historical design conditions may become obsolete during even the initial stages of a building’s expected life span. Changes in climatic design conditions in Madison highlight the importance of considering future climatic changes in building design to ensure that buildings built today meet the performance needs of the future.

1. Introduction

Climatic design conditions are widely used by the building community as environmental parameters informing the size and energy requirements for heating, ventilation and air conditioning (HVAC) systems, along with other building design characteristics (http://ashrae-meteo.info/v2.0/). Climatic design conditions are calculated by the American Society of Heating, Refrigerating and Air-conditioning Engineers (ASHRAE) using historical climate data, representing both mean climatic conditions (e.g. average temperature or precipitation)
as well as the behavior of climatic extremes (e.g. heating and cooling degree hours, or threshold exceedances). However, climate change produces changes in both local mean conditions (IPCC 2021) and the frequency and intensity of extreme weather, including temperature extremes (Rahmstorf and Coumou, 2011, Taylor et al 2012, Vose et al 2017) and precipitation extremes (Easterling et al 2017, Janssen et al 2014). The rapid pace of these changes (IPCC 2021), together with long-expected building life spans (~100 yr), means that buildings designed today will potentially be operating under significantly different climatic design conditions in the future.

Like other aspects of the built and natural environment, building design and operation is expected to change with a warming climate. A warmer future climate will increase the demand for building cooling and decrease the demand for building heating (Hunt and Watkiss 2011, Petri and Caldeira 2015, Rey-Hernández et al 2018, Wang and Chen 2014), with associated impacts on building energy use (Hadley et al 2006, Lebassi et al 2010, Meier et al 2017, Rey-Hernández et al 2018). In addition, the thermal performance of building envelopes, such as window glazing (Gaterell and McEvoy 2005) and wall and roof insulation (Karimpour et al 2015), will be affected by changes in heat and humidity. As the climate warms, natural ventilation may become insufficient for maintaining human comfort for buildings in some cities (Artmann et al 2008, Wang and Chen 2014), which will affect building operation and occupant behavior. These impacts will further change the building heating and cooling loads. In light of these expected changes, architects, engineers and building owners may choose to design buildings differently, by anticipating the future in which buildings will operate.

Heating and cooling loads are the primary design basis for HVAC systems (ASHRAE 2013). These loads are the rates of energy input and removal required to maintain a comfortable and healthy indoor environment. HVAC systems are often sized on heating and cooling loads to ensure their efficiency in a local climate. Improperly sized systems will lead to a higher cost (Riise and Sørensen 2013b), a reduction in the reliability and lifetime of systems (Yau and Pean 2011), lower thermal comfort (Sekhar et al 2018), and an increase in energy consumption (Riise and Sørensen 2013a, Sekhar et al 2018). Outdoor climatic design conditions, especially extreme conditions, are critical factors in calculating heating and cooling loads, and therefore, in designing HVAC systems. The purpose of this study is to develop a method for estimating how climate change may affect these climate design conditions.

While global climate models (GCMs) are useful in projecting general climate trends used in making international mitigation policies, their output is not appropriate for direct use in calculating climate design conditions, for a variety of reasons. First, the spatial resolution of GCMs is often between 100–250 km (Semenov 2007, Semenov and Stratonovitch 2010), which is too coarse to simulate conditions that produce weather extremes at local scales (Sillmann et al 2013). Second, the temporal resolution of GCMs often does not meet the requirement of design condition calculations since the GCMs typically provide data on a daily or monthly scale (Semenov and Stratonovitch 2010, Shen 2017) but the design conditions require hourly data. Third, GCMs often have large biases in their simulation of the amplitude and timing of the diurnal (day and night) cycle (Christopoulos and Schneider 2021, Mcguiffe et al 1999, Yin and Porporato 2017, Ylhäisi and Räisänen 2014), affecting both temperature and humidity metrics. Finally, climate models are biased in their simulation of extreme temperatures for a variety of reasons, including biases in simulation of mean temperature and variability (variations from the mean conditions) (Di Luca et al 2020). In this study, we develop a ‘rescaling’ method that blends observed variations with climate model projections to bypass many of these limitations.

A variety of previous studies have used climate model data in constructing building design data or estimating building energy use (see Jiang et al 2019 for a review). Many of these studies employ a ‘morphing technique’ (Belcher et al 2005) that downscales coarse resolution GCMs to a fine spatial and temporal resolution (Jiang et al 2019, Shen 2017, Zhai and Helman 2019) by shifting (using the expected change in the mean) and rescaling (using the expected change in variance) a particular climatic variable. This technique produces hourly data (Belcher et al 2005), but it may neglect changes in the diurnal cycle (Davy et al 2017, Lindvall and Svensson 2015) and non-symmetric changes to climate variability, which are both observed and projected by climate models (Davy et al 2017, Vose et al 2017). These variations are essential in predicting climate extremes (Griffiths et al 2005, Katz and Brown 1992, Schaeffer et al 2005). In this study, we use a rescaling technique to incorporate changes in both the diurnal cycle and in the probability distribution of expected variability to ensure appropriate rescaling of hourly climate data. This rescaling method is similar to the morphing method since it rescales existing historical data, and as such produces results that are directly relatable to existing climatic design conditions. The use of historical humidity data also ensures that covariances between temperature and humidity are maintained (this is especially important for combined heating/cooling and humidification/dehumidification design conditions). The method provides an advancement on morphing in that it includes expected changes in the diurnal temperature range (Davy et al 2017, Lindvall and Svensson 2015) and accounts for potential non-symmetric changes in variability including changes to extreme events (Kirchmeier-Young et al 2016) that are critical for building climatic design conditions.
This study uses a rescaling methodology to recalculate the climatic design conditions (http://ashrae-meteo.info/v2.0/) produced by ASHRAE for Madison, WI, a mid-sized, four-season city in the Upper Midwestern United States. Climatic design conditions are calculated for four future periods (2021–2040, 2041–2060, 2061–2080 and 2081–2100), and two future greenhouse gas emission scenarios indicated by representative concentration pathways (RCPs), RCP 4.5 and RCP 8.5. RCPs are greenhouse gas concentration trajectories adopted by the Intergovernmental Panel on Climate Change (IPCC) to provide a range of possible climate futures (IPCC 2014, van Vuuren et al 2011). RCP 4.5 refers to an intermediate scenario where emissions peak around 2040, then decline, while RCP 8.5 describes a business-as-usual scenario where emissions increase throughout the 21st century (IPCC 2014, Meinshausen et al 2011). Madison is classified as ASHRAE 169-2013 climate zone 5A, defined as a cool-humid zone. Madison buildings rely on heating through winter and air conditioning for much of the summer. Consequently, the impact of climate change on building design conditions in Madison offers a well-suited case study for this methodology. Note that this study evaluates the effects of climate change, specifically temperature change, on climatic design conditions. While climatic design conditions are used for building design, we do not evaluate building design directly, so other factors such as building types, construction, and use characteristics are not evaluated in this work.

This study is organized as follows: section 2 describes the data used in the study; section 3 presents the methodology for calculating ASHRAE-equivalent design metrics for future conditions; section 4 applies this methodology to Madison, Wisconsin, and section 5 summarizes the results and provides conclusions and discussion.

2. Data

Two main data sets were used in this analysis, historical measurement data and the University of Wisconsin Probabilistic Downscaling (UWPD) model data for the future climate. Historical measurement data were obtained from the Integrated Surface Data (ISD) (available at https://ncdc.noaa.gov/isd/products); this is the same data used by ASHRAE to calculate temperature- and humidity-related design metrics. Hourly dry-bulb temperatures and dewpoint temperatures (DP) were obtained from 1986–2010 for the Madison/Dane County station (WMO: 726410). For quality control, the suspect and erroneous values flagged in the ISD document (NOAA 2018), as well as the missing values were removed. Duplicate times were replaced with the average of contemporaneous observations, and individual hourly outliers were replaced by averaging data on either side of the outlier.

The UWPD data set (Notaro et al 2014, Wu et al 2019) is a statistically downscaled climate data product produced via a probabilistic downscaling methodology. The UWPD data set uses vector generalized linear models (Yee and Stephenson 2007) to predict the daily varying probability density function (PDF) of station observations (daily maximum temperature (TMAX) and minimum temperature (TMIN), and precipitation) from large-scale climatic variables that are produced by GCMs from phase 5 of the Coupled Model Intercomparison Project (Taylor et al 2012). Daily PDFs are then integrated into cumulative distribution functions (CDFs) and averaged into 12 monthly climatological CDFs for a given time period. Each of these 12 monthly CDFs represents the climatological CDF of daily TMAX and TMIN, and precipitation. We used the CDFs of TMAX and TMIN in this analysis. The UWPD probability distributions are provided at a spatial resolution of 0.1° × 0.1°, and they cover the eastern United States (east of the Rocky Mountains) and some of southern Canada. The data set is provided for a historical scenario that runs from 1950–2005 and for future scenarios that run from 2006–2100. The UWPD provides future data under a stringent mitigation scenario (RCP 2.6), two intermediate scenarios (RCP 4.5 and RCP 6.0) and a business-as-usual scenario (RCP 8.5).

While a variety of downscaling techniques could be used to relate large-scale climatic conditions (i.e. those produced by a GCM) to local-scale climatic variations (e.g. point measurements of daily maximum or minimum temperature), the UWPD is somewhat unique in its use of a probabilistic approach. Most statistical downscaling approaches recognize that large-scale meteorological patterns such as jet stream variations or other atmospheric circulations are fundamental to the occurrence of local-scale variations such as temperature extremes at a point (Grotjahn et al 2016). The UWPD probabilistic approach also recognizes that those large-scale conditions cannot entirely determine the local-scale conditions at a particular location since other factors on smaller scales such as topography, land cover and other unresolved local processes also affect local-scale conditions (Aalto et al 2014). The UWPD data approach uses a PDF to quantify the range of local-scale values that could have occurred, given the large-scale conditions for that particular day, and therefore accounts for the uncertainty in using large-scale conditions to explain the local-scale variable (Kirchmeier-Young et al 2016). A key result for this study is that the PDF retains the full range of local-scale variability, including the extremes that are often muted by GCMs or in other downsampling methods (Belcher et al 2005, Sillmann et al 2013). Furthermore, the UWPD PDFs can be used to rescale a set of existing observations to a
different climate scenario while maintaining the same event probability (Kirchmeier-Young et al. 2016). Here, we apply the rescaling to the ISD data.

3. Methods

For the climatic design conditions, we used the 2013 ASHRAE Climatic Conditions chart (http://ashrae-meteo.info/v2.0/; hereinafter referred to as the ASHRAE chart) as a reference, with a focus on certain metrics related to temperature and humidity. We followed ASHRAE's calculation methods described in chapters 1 and 14 of the 2013 ASHRAE Handbook (ASHRAE 2013). The calculation method and resulting climatic design conditions for the historical period (1986–2010) are provided in the supplemental material (https://stacks.iop.org/ERIS/2/025007/mmedia). Using the same calculation methods ensures that future changes in building design characteristics are due to anticipated climatic changes instead of artifacts from different calculation methods (i.e. calculation differences attributable to small differences between the ASHRAE algorithms and our calculation methods).

3.1. Rescaling historical hourly data to future conditions

To calculate future hourly data with a realistic diurnal cycle, variability (including extremes) and co-variability between variables, we used the UWPD monthly CDFs to rescale ISD historical hourly data to be representative of future climatic conditions using the following four steps (figure 1): (1) obtaining daily resolved climatological CDFs from the UWPD data; (2) rescaling observed TMAX and TMIN from historical to future conditions using the UWPD CDFs; (3) obtaining the fractional diurnal range that relates historical hourly temperatures to daily TMAX and TMIN and (4) calculating future hourly data using the rescaled TMAX and TMIN (step 2) and the diurnal fractions obtained in step 3.

Step 1: the UWPD data set contributes monthly climatological CDFs of daily TMAX and TMIN for a particular time period. To obtain daily climatological CDFs, we linearly interpolated the monthly UWPD CDFs (which are representative of mid-month conditions) to a given calendar day using,

\[ CDF_{\text{day}} = b_{\text{day}} \times CDF_{\text{month}} + (1 - b_{\text{day}}) \times CDF_{\text{month}}, \]  

where parameter \( b \) is the temporal fractional scaling for each day. The value of \( b \) would be equal to 1 for the days that are exactly in the middle of the month, and approach 0.5 for days at the beginning and end of the month. This method produces a unique and smoothly varying climatological CDF for each calendar day, and avoids abrupt jumps in the CDF that would occur near the end of the month, say, from 1 December to 1 January. As an example, the resulting CDF of TMAX for say, 1 January (see figure 2), would represent the range of possible values of TMAX that one might expect on 1 January for a given climatological time period, say, 1981–2010 (red curve in figure 2) or 2041–2060 (black curve in figure 2).

Step 2: historical daily TMAX and TMIN are rescaled to future climatic conditions via quantile remapping that uses the daily climatological CDFs from the UWPD. This process is illustrated in figure 2. First, a given day’s TMAX or TMIN was calculated from the hourly ISD data (defined as the maximum or minimum from midnight to 11 pm). The UWPD historical CDF is used to calculate the non-exceedance probability for a given day’s TMAX or TMIN (red dashed line in figure 2). The non-exceedance probability here is defined as the probability of TMAX or TMIN for a given day taking a value that is less than or equal to the actual TMAX or
Figure 2. Graphical example of the rescale technique used for TMAX and TMIN, applied to the historical TMAX for 1 January, 1986. Red curve shows the climatological CDF for 1981–2010, and the black curve shows the future (2041–2060) CDF under the RCP 8.5 scenario. For the given day’s TMAX in historical record (0 °C), the exceedance probability is determined from the historical CDF (red dashed line), and then rescaled using the same exceedance probability for the future CDF (blue arrow) to obtain the future TMAX (black dashed line). CDFs in this example are from the GFDL-CM3 model.

TMIN value for that given day. This non-exceedance probability (blue line in figure 2) is then used to calculate the corresponding future non-exceedance temperature (black dashed line in figure 2) from the UWPD future CDF. This process is repeated for all days in the historical data record (1986–2010), and separately for each emission scenario, model and time period used herein. Note that the rescaling procedure produces the same temporal sequence of natural variability as the observed record, but allows for changes in the diurnal range in the characteristics of daily variability. The use of the same sequence of ISD data ensures that natural variability does not unduly mask or alias on expected climatic changes.

Step 3: the previous step provides daily projections of future TMAX and TMIN, whereas many of the ASHRAE metrics require hourly data. To calculate the relationship between historical hourly and daily values, a fractional diurnal range was calculated from the historical ISD data and stored for each hour of each day in the historical record. The fractional diurnal range \( a_{\text{hour}} \) for a given day was computed using,

\[
a_{\text{hour}} = \frac{(T_{\text{hour}} - T_{\min\text{day}})}{(T_{\max\text{day}} - T_{\min\text{day}})},
\]

with hourly temperature \( T_{\text{hour}} \), daily TMAX and TMIN \( T_{\max\text{day}} \) and \( T_{\min\text{day}} \) obtained from the historical ISD data. The use of historical records to compute the diurnal fraction ensures that the diurnal cycle is determined by nature, rather than by a potentially biased model representation of the diurnal cycle (Sillmann et al 2017).

Step 4: assuming that the observed fractional diurnal range \( a_{\text{hour}} \) remains the same in the future, we transform (3.2) to obtain estimates of future hourly temperature:

\[
T_{\text{hour}} = a_{\text{hour}} \times T_{\max\text{day}} + (1 - a_{\text{hour}}) \times T_{\min\text{day}}.
\]

Note that (3.3) assumes that the fractional diurnal range, but not the diurnal range itself (see step 3), remains constant under future climatic conditions. This ensures a realistic representation of the expected changes in the diurnal range (Davy et al 2017, Lindvall and Svensson 2015).

This approach provides hourly data in the same format as historical hourly data. Figure 3 shows an example time series of historical (1986–2010) hourly temperature (blue line) and mid-21st century (2041–2060) hourly temperature (red line) under the RCP 8.5 scenario. Only the first ten days in January and July were presented to clearly see the diurnal cycle. The figure demonstrates how our methodology alters the mean and diurnal temperatures but retains historical natural variability.

In addition to the temperature-related metrics, the ASHRAE chart includes metrics that depend on humidity (dewpoint temperature, wet bulb temperature and humidity ratio) and on the covariation between humidity and temperature. The UWPD does not provide projected humidity metrics, so future humidity metrics are calculated by assuming that there will be no change in relative humidity. Future humidity metrics are then
Figure 3. Time series of hourly temperature for historical record (red line) and for future condition (black line). Historical hourly temperature for the first ten days in January (left) and July (right) of 1986 is obtained from ISD, and then rescaled using the UWPD data set for mid-21st century (2041–2060), under the RCP 8.5 emission scenario. Future temperature is averaged from 24 GCMs.

Table 1. List of models used for different emission scenarios.

| Model name       | RCP 4.5 | RCP 8.5 | Reference                      |
|------------------|---------|---------|--------------------------------|
| ACCESS1-0        | X       |         | (Ackerley and Dommenget 2016)  |
| ACCESS1-3        | X       | X       | (Collier and Uhe 2012)         |
| CMCC-CESM        |         | X       | (Vichi et al 2011)             |
| CMCC-CM          | X       | X       | (Scoccimarro et al 2011)       |
| CMCC-CMS         | X       | X       | (Scoccimarro et al 2011)       |
| CNRM-CM3         | X       | X       | (Voldoire et al 2013)          |
| CSIRO-MK3-6-0    | X       | X       | (Collier et al 2011)           |
| CanESM2          | X       | X       | (Chylek et al 2011)            |
| GFDL-CM3         | X       |         | (Donner et al 2011)            |
| GFDL-ESM2G       | X       | X       | (Dunne et al 2012)             |
| GFDL-ESM2M       |         | X       | (Dunne et al 2012)             |
| HadGEM2-CC       | X       | X       | (Collins et al 2011)           |
| IPSL-CM5A-LR     | X       | X       | (Dufresne et al 2013)          |
| IPSL-CM5A-MR     | X       | X       | (Dufresne et al 2013)          |
| IPSL-CM5B-LR     | X       | X       | (Dufresne et al 2013)          |
| MIROC-ESM        | X       | X       | (Watanabe et al 2011)          |
| MIROC-ESM-CHEM   | X       | X       | (Watanabe et al 2011)          |
| MIROC5           | X       |         | (Watanabe et al 2010)          |
| MPI-ESM-LR       | X       | X       | (Block and Mauritsen 2013)     |
| MPI-ESM-MR       | X       | X       | (Block and Mauritsen 2013)     |
| MRI-CGCM3        | X       | X       | (Yukimoto et al 2012)          |
| MRI-ESM1         | X       |         | (Yukimoto et al 2011)          |
| NorESM1-M        | X       | X       | (Bentsen et al 2013)           |
| inmcm4           | X       | X       | (Volodin et al 2010)           |

determined by applying the Clausius–Clapeyron relationship to future hourly temperatures, and then scaling the result using historical relative humidity. Our assumption of constant relative humidity may overestimate the expected changes in variables related to wet-bulb temperatures because the surface relative humidity is predicted to decrease in the future (Byrne and O’Gorman 2016). However, using Byrne and O’Gorman’s scaling, we found that the overestimation is marginal compared to the impact of climate change (see supplementary material). In addition, assuming that there will be no change in relative humidity ensures that the historical covariation between temperature and humidity variables is maintained for future conditions.

3.2. Producing design metrics for future conditions

The hourly future temperatures and DP were used to calculate temperature- and humidity-related design metrics using the ASHRAE formulae described in chapters 1 and 14 of the 2013 ASHRAE Handbook (ASHRAE 2013). The process of calculating design metrics was repeated for each of the GCMs under RCP 4.5 and RCP 8.5 (listed in Table 1), each associated with a portfolio of future design conditions. These variables are averaged across the GCMs to produce the final design metrics for a given time period under a given emission scenario.
4. Building design conditions in Madison, Wisconsin

Climatic design charts parallel to the ASHRAE chart (http://ashrae-meteo.info/v2.0/) were calculated for Madison, Wisconsin, for four periods (2021–2040, 2041–2060, 2061–2080 and 2081–2100), under the business-as-usual scenario (RCP 8.5) and the intermediate emission scenario (RCP 4.5). The design charts are provided in the supplementary material. In the discussion below, we focus on three main design conditions: annual heating and humidification design conditions, annual cooling and dehumidification design conditions, and heating and cooling degree days. These future design conditions are compared with the latest version of ASHRAE design conditions calculated from the temperature from 1990–2014. Table 2 presents the changes in the design conditions by future periods, with a 95% confidence limit as determined by a standard two-tailed T-test applied to the range of model projections. Overall, changes in building climatic design conditions were consistent with the expectations of a warmer climate.

4.1. Heating and humidification design conditions

Building heating and humidification systems are designed to meet the coldest and driest weather conditions, corresponding to the maximum heating load, and determined by the level of heating needed to provide comfort to building inhabitants. Building heating and humidification design conditions or design thresholds are captured by dry-bulb temperature (DB) and the pairing of DP with mean coincident dry-bulb temperatures (MCDB) corresponding to 99.6% and 99% annual cumulative frequency of occurrence. The 99.6% and 99% indicate values for which the corresponding weather element is less than the design condition for 35 and 88 h per year, respectively, and the 99.6% describes a more extreme condition than the 99% (ASHRAE 2013).

Current heating and humidification thresholds provided by ASHRAE for future DB thresholds, calculated from projected temperature, and their associated changes, are shown in figure 4 and table 2. The 99.6% and 99% DB metrics show the thresholds of extremely cold temperatures and are often used in sizing heating equipment (ASHRAE 2013). Figure 4 shows that under both RCP 4.5 and RCP 8.5 scenarios, the DB thresholds increase by about 2.5 °C by 2021–2040, but thereafter the warming continues roughly linearly in the RCP 8.5 scenario, but begins to level off in the RCP 4.5 scenario. Consequently, under the intermediate RCP 4.5 scenario, extreme cold conditions in Madison are projected to warm by about 3.8 °C by mid-century and about 5.3 °C by late-century. Under the RCP 8.5 business-as-usual scenario, extreme cold conditions are projected to warm by about 4.5 °C and 9 °C by mid and late-century, respectively.

Similar increases can be seen in humidification thresholds, represented by the 99.6% and 99% DP-MCDB. These values provide thresholds for extremely cold and dry conditions and are used in the design of the cold season humidification applications (ASHRAE 2013). Both the DP and MCDB are projected to increase by about 2.5 °C by 2021–2040 under both RCP scenarios (table 2). Like the DB projections, under the RCP 8.5 scenario the DP continues to increase by 2 °C–3 °C per 20 yr period through to the end of the 21st century, while under the RCP 4.5 scenario the DP changes begin to level off (figure 4). These changes suggest that under the intermediate RCP 4.5 scenario, humidification requirements in Madison will be reduced (less dry) by about 3.8 °C and 5.2 °C (as measured by dewpoint temperature) by mid and late-century; and under the RCP 8.5 business-as-usual scenario, the reduction increases to 4.5 °C and 8.7 °C.

In both heating and humidification thresholds, the values corresponding to 99% in a period are about the same as values corresponding to 99.6% in the next period. For example, 99% DB in 1990–2014 (−18.5 °C) is about the same as the 99.6% DB in 2021–2040 (−18.7 °C). This means that as the climate warms, the less extreme cold condition (99%) given by ASHRAE today is actually the most extreme cold condition (99.6%) that will be faced in 20 yr. Another way to interpret the change is by noting that the annual duration of temperatures lower than about −18.5 °C will decrease from 88 h (99%) in 1990–2014 to 35 h (99.6%) in 2021–2040, and will decrease in duration even more in the following decades.

4.2. Cooling and dehumidification design conditions

Building cooling and dehumidification systems are designed to meet the hottest, most humid weather conditions, corresponding to the maximum cooling load, and determined by the level of cooling needed to provide a thermally comfortable indoor environment. Cooling and dehumidification metrics are captured by cooling variables corresponding to 0.4%, 1% and 2% annual cumulative frequency of occurrence. The 0.4%, 1% and 2% indicate values for which the corresponding weather element exceeds the design condition for 35, 88 and 175 h per year, respectively (ASHRAE 2013). Here, we focus on two more extreme conditions, the 0.4% and 1% exceedance thresholds. Current and future cooling and dehumidification design conditions and their changes are presented in figure 5 and table 2.

Cooling design conditions represent the warmest conditions that normally occur during hot sunny days (ASHRAE 2013). They highlight the sensible loads and are used in applications where room humidity control is not essential (Bellia et al 2000). Cooling equipment, such as chillers or air-conditioning units, are often sized
### Table 2. Changes in the future climatic design conditions with 95% confidence limits.

|                          | 1990–2014 | Δ by 2021–2040 | Δ by 2041–2060 | Δ by 2061–2080 | Δ by 2081–2100 |
|--------------------------|-----------|----------------|----------------|----------------|----------------|
|                          | RCP 4.5   | RCP 8.5        | RCP 4.5        | RCP 8.5        | RCP 4.5        |
| DB 99.6% DB              | −21.3     | 2.5 ± 0.73     | 2.6 ± 0.54     | 3.9 ± 0.83     | 4.5 ± 0.84     |
| DB 99% DB                | −18.5     | 2.5 ± 0.7     | 2.6 ± 0.51     | 3.8 ± 0.76     | 4.4 ± 0.79     |
| DP 99.6% DP              | −26.5     | 5.1 ± 0.54     | 2.5 ± 0.52     | 3.8 ± 0.81     | 4.4 ± 0.78     |
| DP 99% DP                | −23.7     | 4.1 ± 0.56     | 2.7 ± 0.45     | 3.8 ± 0.73     | 4.3 ± 0.75     |
| DP-MCDB 99% MCDB         | −20.4     | 4.4 ± 0.88     | 2.4 ± 0.56     | 3.9 ± 0.92     | 4.4 ± 0.77     |
| DB 0.4% DB               | 31.9      | 1.7 ± 0.33     | 1.3 ± 0.29     | 2.3 ± 0.5      | 3 ± 0.46      |
| DB 1% DB                 | 30.3      | 3.1 ± 0.34     | 1.8 ± 0.31     | 2.3 ± 0.47     | 3.1 ± 0.43     |
| DP-MCWB 1% MCWB          | 23.4      | 1.5 ± 0.25     | 1.7 ± 0.26     | 2.1 ± 0.41     | 2.7 ± 0.36     |
| DB 0.4% MCDB             | 30.1      | 0.4 ± 0.35     | 1.4 ± 0.35     | 1.9 ± 0.5      | 2.6 ± 0.45     |
| DP 1% MCDB               | 25        | 2 ± 0.55       | 1.5 ± 0.26     | 2 ± 0.45       | 2.7 ± 0.41     |
| DP-MCWB 1% MCDB          | 28.5      | 1.6 ± 0.31     | 1.6 ± 0.31     | 2 ± 0.47       | 2.7 ± 0.42     |
| HDD_18.3                 | 3935      | −448 ± 91      | −455 ± 82      | −655 ± 106     | −786 ± 117     |
| CDD_18.3                 | 356       | 322 ± 68       | 332 ± 52       | 248 ± 55       | 306 ± 74       |

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**Δ** by 2021–2040, Δ by 2041–2060, Δ by 2061–2080, Δ by 2081–2100.
at 0.4%, 1% and 2% DB and corresponding humidity conditions on the hottest days indicated by MCWB. Exceedance DB and MCWBs are projected to increase throughout the 21st century, but like heating conditions, the rate of increase varies under the two RCP scenarios. From 1990–2014 to 2021–2040, the DB-MCWB exceedance temperatures are projected to increase by about 1.5 °C (under RCP 4.5) and 1.7 °C (under RCP 8.5). After that, the increase under RCP 8.5 continues to grow at a rate of 1.5 °C–1.6 °C per 20 yr period, while under the RCP 4.5 scenario, these metrics increase at a rate of 0.8 °C–0.3 °C per 20 yr period. Consequently, under the intermediate RCP 4.5 scenario, extreme hot conditions in Madison are projected to become about 2.3 °C hotter by mid-century and about 3.2 °C hotter by late-century; under the RCP 8.5 business-as-usual scenario, these conditions are projected to increase by about 3.1 °C and 6.1 °C.

Where humidity control is important, 0.4%, 1% and 2% DP, and the MCDB are more appropriate design conditions to consider (Bellia et al 2000). These design conditions represent the extreme moisture content of outdoor air and are used in humidity control applications, such as desiccant cooling and dehumidification, cooling-based dehumidification and outdoor air ventilation systems (ASHRAE 2013). The DP-MCDB pairs are projected to increase throughout the 21st century (table 2), and like other temperature metrics the rate of increase under RCP 4.5 is less than that under RCP 8.5. Figure 5 shows that the DP exceedance metrics are projected to increase by about 1.5 °C under either scenario by 2021–2040. Thereafter, under the intermediate RCP 4.5 scenario, extreme humid conditions in Madison will become 2.3 °C more humid by mid-century and 3.3 °C more humid by late-century. Under the RCP 8.5 business-as-usual scenario, the values will increase by about 3.1 °C and 6.2 °C by mid and late-century, respectively. The business-as-usual scenario also shows that the 0.4% DP-MCDB in 2081–2100 will exceed current values at any U.S. station listed in the 2017 ASHRAE chart, suggesting that the most extreme humid condition in Madison in the late-21st century could be more severe than the current situation in any U.S. city.

The evaporation design conditions represent the extremes of the total sensible plus latent heat of the outdoor air. These conditions consider a combination of the heat absorption capacity of dry air and the capacity of the evaporated water in the air. The 0.4%, 1% and 2% WB and the corresponding MCDB are used for the design
of cooling towers, evaporative coolers and outdoor air ventilation systems (ASHRAE 2013). By 2021–2040, both the 0.4% and 1% metrics in the WB-MCDB exceedance thresholds will increase by about 1.5 °C under either scenario. Under an intermediate scenario, the WB-MCDB in Madison will increase by about 2 °C by mid-century and by about 2.9 °C by late century. Under a business-as-usual scenario, the values will increase by about 2.7 °C and 5.6 °C by mid and late-century, respectively. Like the 0.4% DP-MCDB, the 0.4% WB-MCDB in Madison in the late-21st century will exceed the current WB-MCDB values at any U.S. station in the 2017 ASHRAE chart, which suggests a significant increase in extreme total heat (sensible plus latent) of the outdoor air in Madison.

### 4.3. Degree days

Degree days are defined as the sum of the differences between daily temperatures and a reference temperature in a given time, and as such, they capture both the extremity and duration of outdoor temperatures (CIBSE 2006). Two reference temperatures, 18.3 °C (65 °F) and 10 °C (50 °F) are considered by ASHRAE. The 18.3 °C threshold is the standard reference temperature used in the U.S. and is based on the assumption that when the outdoor temperature is 18.3 °C, no cooling or heating is needed to maintain thermal comfort (EIA 2021). This reference temperature is widely used to study the impact of climate change on the building cooling and heating energy demand (Chen et al 2007, Li et al 2021, Petri and Caldeira 2015, Sivak 2013). ASHRAE uses 18.3 °C and 10 °C for heating degree day (HDD) and cooling degree day (CDD), respectively, when defining climate zones (ASHRAE 2013). Since HDD and CDD are the sum of absolute temperature differences, they are provided with a unit of °C, and larger values indicate higher demand for heating or cooling.

Discussion below focuses on the standard reference temperature 18.3 °C.

Our results showed significant changes in HDD and CDD in Madison (table 2 and figure 6). Under the RCP 8.5 scenario, annual HDD is projected to decrease by about 11% per period, while annual CDD will increase by about 50% by 2021–2040, and thereafter will increase by about 30% in each of the following 20 yr periods. Consequently, annual HDD in Madison is projected to decrease by 20% by mid-century and by 38% by late-century; annual CDD is projected to double by mid-century and triple by late-century. The changes are less pronounced under RCP 4.5, which projects a 17% and 23% reduction in HDD by mid and late-century, respectively, and a CDD increase of 1.7 times its current value by mid-century and double its current value by late-century.

HDD\textsubscript{18.3} and CDD\textsubscript{18.3} were found to have high correlations with energy consumed for building heating and cooling (and cooling) (Quayle and Diaz 1980, Suckling and Stackhouse 1983, Timmer and Lamb 2007), so we compared future HDD\textsubscript{18.3} and CDD\textsubscript{18.3} in Madison with the current HDD\textsubscript{18.3} and CDD\textsubscript{18.3} listed in ASHRAE’s design table to present a general view of future building heating and cooling in Madison. Under a business-asusual RCP 8.5 scenario, building heating and cooling in Madison is projected to resemble the current heating demand in Chicago, IL, and cooling demand in Baltimore, MD, by mid-century; by late-century, Madison is projected to experience the current heating demand in St. Louis, MO, and cooling demand in Augusta, Georgia. Note that this comparison only shows changes from a climate perspective. In reality, the results can change depending on other factors, such as building type and characteristics, and energy sources.

Monthly HDDs and CDDs are shown in figure 6. In Madison, January and July have been the peak demand month for heating (the largest HDD) and cooling (the largest CDD), respectively, and will remain as the peak demand month. From 1990–2014 to 2021–2040, a similar decrease in HDD and increase in CDD are seen under RCP 4.5 and RCP 8.5 scenarios, but after that the changes continue approximately linearly under RCP 8.5 but level off under RCP 4.5. Beyond mid-century, further changes under RCP 4.5 are marginal. In addition, both RCP scenarios project that HDD will decrease most in January and CDD will increase most in July. Consequently, by the end of the 21st century the seasonal variations in HDD will reduce from 778 °C to 647 °C.
under RCP 4.5 and to 550 °C under RCP 8.5, respectively, and seasonal variations in CDD will increase from 122 °C to 215 °C under RCP 4.5 and to 303 °C under RCP 8.5, respectively. Furthermore, by the end of the century, cooling seasons in Madison, defined as the month where CDD18.3 exceeds HDD18.3, will extend from three months (early June to late August) in 1990–2014 to four months (late May to late September) under the RCP 4.5 and to five months (early May to early October).

5. Conclusions and discussion

This study presents a method for evaluating the effects of climate change on climatic building design conditions. The design conditions are determined by climatic extremes, so their calculations require a realistic representation of daily and hourly variability. These requirements place stringent constraints on climate projections used to evaluate future conditions. To develop these climatic design conditions, a rescaling methodology is developed that produces hourly temperature projections. First, the observed daily maximum and minimum temperatures are separately projected to future conditions through the UWPD projection, allowing for expected future changes in the diurnal temperature range and characteristics of daily variability. Next, the historical hourly ‘diurnal fraction’ is calculated and applied to projected daily maximum and minimum temperatures to produce future hourly temperature data. This rescaling method ensures that daily variability and co-variability of local-scale variables is preserved (Kirchmeier-Young et al 2016), future changes in the diurnal temperature range (Davy et al 2017, Lindvall and Svensson 2015) are captured, and that realistic hourly variations are maintained.

We used the rescaling method to produce design conditions for Madison, Wisconsin, for four future periods (2021–2040, 2041–2060, 2061–2080 and 2081–2100) under business-as-usual (RCP 8.5) and intermediate (RCP 4.5) scenarios, and compared the results to the present design conditions given by ASHRAE (1990–2014). Our analysis focuses on two types of design conditions: exceedance thresholds used for sizing HVAC systems and heating/cooling degree days used for estimating building heating and cooling demand. Overall, the climatic design conditions change in ways that are consistent with a warming climate. Under the business-as-usual RCP 8.5 scenario, the changes are approximately linearly throughout the 21st century, while under the intermediate RCP 4.5 scenario, the changes begin to level off after mid-century. Under the RCP 4.5 (RCP 8.5) scenario, exceedance thresholds of heating and humidification conditions in Madison are projected to become 3.8 °C (4.5 °C) warmer by mid-century and about 5.3 °C (9 °C) warmer by late-century; exceedance thresholds of cooling and dehumidification conditions are projected to increase by about 2.3 °C (3.1 °C) by mid-century and about 3.2 °C (6.1 °C) by late-century. These increases suggest that the extreme cold conditions in Madison will become less severe in the future, while the extreme hot and humid conditions will become more severe. In terms of degree days, lower HDD and higher CDD are expected in Madison. Under a business-as-usual scenario, by mid-century, building heating and cooling in Madison will be similar to the current heating demand in Chicago, Illinois and cooling demand in Baltimore, Maryland, respectively; by late-century, building heating and cooling in Madison could resemble the current heating demand in St. Louis, MO and cooling demand in Augusta, GA. HDD and CDD both see their largest change in their peak month, January for HDD and July for CDD. Cooling seasons are projected to extend from three months to five months in Madison by late-century.

The methodology presented herein provides a novel method for incorporating climate change into the calculation of climatic building design conditions, and for utilizing multiple large-scale models and future emission scenarios in order to assess uncertainty. While our analysis is based on the UWPD data set, which has limited spatial extent (the eastern United States and some of southeastern Canada), the methods herein could be easily adapted to other locations with similar hourly climate data. These data could be used to develop bias corrections for CDFs of daily maximum and minimum temperature (e.g. Vano et al 2020, Xu and Wang 2019), and the result applied to climate model output.

The expected changes in climatic building design conditions may have a variety of implications for actual building design that vary with the impact and time scale. Many HVAC systems have a much shorter life expectancy than the building itself, so HVAC sizing and capacity might consider climatic changes over the next two or three decades. Changes in extremes (specifically threshold exceedance temperatures and humidity) are important for HVAC system capacity, and suggest a shift towards reduced heating and humidification, and increased cooling and dehumidification requirements. Proper consideration of HVAC sizing can help avoid a variety of problems, such as higher cost, lower efficiency and reliability (Riise and Sørensen 2013a), lower thermal comfort (Sekhar et al 2018) and higher energy consumption (Riise and Sørensen 2013a, Sekhar et al 2018). While these are important considerations, the expected HVAC system replacement time scale may be comparable to the time scale of expected climatic changes. Therefore, the motivation for reconsidering HVAC design may be to improve efficiency rather than to avoid potential future building redesign.
As the climate continues to warm through mid-century, changes in climatic building design conditions may have more implications for structural design, such as ducting capacity, building envelope, insulation considerations or even building function and occupant behavior. These are not easily changed after building design, so a design strategy emphasizing climate-adaptive buildings (Urge-Vorsatz et al. 2014) may avoid costs associated with future remodel or building repurposing. By considering the future climate conditions that buildings are likely to experience, architects may adjust their strategies on building envelopes, massing and orientation measures from the early stage to improve insulation and optimize building energy efficiency (De Cian et al. 2019). This methodology can also be used to update design conditions or standards in other built infrastructures that are often affected by climate-induced extremes, such as transportation systems (Ataei et al. 2010, Gallivan et al. 2009, Savonis et al. 2009), electric grids (Dale et al. 2018) and drainage systems (Ashley et al. 2005, Nie et al. 2009).

Ultimately, a ‘one size fits all’ response to changing building design conditions does not seem helpful since building design is an iterative process with numerous considerations. The results from this study call attention to the need for future climatic building design conditions as one of those considerations. Making design conditions climate-adaptive is the first and essential step to making our built infrastructure climate-adaptive in the face of more extreme weather and warmer climates (Stewart and Deng 2015).

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Data availability statement

The data that support the findings of this study are available upon reasonable request from the authors.

Conflict of interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the findings of this study.

ORCID iDs

Gesangyangji https://orcid.org/0000-0002-2553-1022

References

[Aalto et al. 2014] Aalto J, le Roux P C and Luoto M 2014 The meso-scale drivers of temperature extremes in high-latitude Fennoscandia Clim. Dyn. 42 237–52
[Ackerley and Dommenger 2016] Ackerley D and Dommenger D 2016 Atmosphere-only GCM (ACCESS1.0) simulations with prescribed land surface temperatures Geosci. Model Dev. 9 2077–98
[Artmann et al. 2008] Artmann N, Gyalistras D, Manz H and Heiselberg P 2008 Impact of climate warming on passive night cooling potential Build. Res. Inf. 36 111–28
[Ashley et al. 2005] Ashley R M, Balmborfh D J, Saul A J and Blansky J D 2005 Flooding in the future—predicting climate change, risks and responses in urban areas Water Sci. Technol. 52 265–73
[ASHRAE 2013] ASHRAE 2013 2013 ASHRAE Handbook (Fundamentals) (Atlanta, GA: ASHRAE, 2013) [2013]
[Ataei et al. 2010] Ataei N, Stearns M and Padgett J E 2010 Response sensitivity for probabilistic damage assessment of coastal bridges under surge and wave loading Transport. Res. Rec. 93–101
[Belcher et al. 2005] Belcher S, Hacker J and Powell D 2005 Constructing design weather data for future climates Build. Serv. Eng. Res. Technol. 26 49–61
[Bellia et al. 2000] Bellia L, Mazzei P, Minichiello F and Palombo A 2000 Outdoor-air design conditions relating to the capacity of air-conditioning systems Int. J. Energy Res. 24 121–35
[Bentsen et al. 2013] Bentsen M et al. 2013 The Norwegian Earth system model, NorESM1-M: I. Description and basic evaluation of the physical climate Geosci. Model Dev. 6 687–720
[Block and Mauritsen 2013] Block K and Mauritsen T 2013 Forcing and feedback in the MPI-ESM-LR coupled model under abruptly quadrupled CO2 J. Adv. Model. Earth Syst. 5 676–91
[Christopoulos and Schneider 2021] Christopoulos C and Schneider T 2021 Assessing biases and climate implications of the diurnal precipitation cycle in climate models Geophys. Res. Let. 48 e2021GL095017

[Chylek et al 2011] Chylek P, Li J, Dubey M K, Wang M and Lesins G 2011 Observed and model simulated 20th century arctic temperature variability: Canadian Earth system model CanESM2 Atmos. Chem. Phys. Discuss. 11 22893–907

[De Cian et al 2019] De Cian E, Pavanello F, Randazzo T, Mistry M N and Davide M 2019 Households’ adaptation in a warming climate. Air conditioning and thermal insulation choices Environ. Sci. Pol. 100 136–57

[Collier and Uhe 2012] Collier M and Uhe P 2012 CMIP5 datasets from the ACCESS1.0 and ACCESS1.3 coupled climate models CAWCR Technical Report No. 059 The Centre for Australian Weather and Climate Research

[Collier et al 2011] Collier M et al 2011 The CSIRO-Mk3-6-0 atmosphere-ocean GCM: participation in CMIP5 and data publication 19th Int. Congress on Modelling and Simulation (Perth, Australia, 12–16 December 2011) (Modelling and Simulation Society of Australia and New Zealand Inc) retrieved from http://hdl.handle.net/102.100.100/102077?index=1

[Collins et al 2011] Collins W J et al 2011 Development and evaluation of an Earth-system model—HadGEM2 Geosci. Model Dev. 4 1031–75

[Dale et al 2018] Dale L, Carnall M, Wei M, Fitts G and Lewis McDonald S 2018 Statewide Summary Report, California’s Fourth Climate Change Assessment SUMCCCA4-2018-013. California Governor’s Ofce of Planning and Research, Scripps Institution of Oceanography, California Energy Commission, California Public Utilities Commission

[Davy et al 2017] Davy R, Esau I, Chernokulsky A, Otten S and Zilitinkevich S 2017 Diurnal asymmetry to the observed global warming Int. J. Climatol. 37 79–93

[Donner et al 2011] Donner I J et al 2011 The dynamical core, physical parameterizations, and basic simulation characteristics of the atmospheric component AM3 of the GFDL global coupled model CM3 J. Clim. 24 3484–519

[Dufresne et al 2013] Dufresne J L et al 2013 Climate change projections using the IPSL-CM5 Earth system model: from CMIP3 to CMIP5 Clim. Dyn. 40 2123–65

[Dunne et al 2012] Dunne J P et al 2012 GFDL’s ESM2 global coupled climate-carbon Earth system models: Physical formulation and baseline simulation characteristics J. Clim. 25 6646–65

[Easterling et al 2017] Easterling D R et al 2017 Precipitation change in the United States Climate Science Special Report: Fourth National Climate Assessment (Washington, DC: U.S. Global Change Research Program) 207–30

[EIA 2021] EIA 2021 Units and calculators explained, degree days retrieved from https://eia.gov/demandexplained/units-and-calculators/degree-days.php

[Gallivan et al 2009] Gallivan F, Ang-Olson J and Turchetta D 2009 Integrating climate change into state and regional transportation plans Transport. Res. Rec. 2119 1–9

[Gaterell and McEvoy 2005] Gaterell M R and McEvoy M E 2005 The impact of climate change uncertainties on the performance of energy efficiency measures applied to dwellings Energy Build. 37 982–95

[Griffiths et al 2005] Griffiths G M et al 2005 Change in mean temperature as a predictor of extreme temperature change in the Asia-Pacific region Int. J. Climatol. 25 1301–30

[Grotjahn et al 2016] Grotjahn R et al 2016 North American extreme temperature events and related large scale meteorological patterns: a review of statistical methods, dynamics, modeling, and trends Climate Dynamics vol 46 (Berlin: Springer)

[Hadley et al 2006] Hadley S W, Erickson D J, Hernandez J L, Broniak C T and Blasing T J 2006 Responses of energy use to climate change: a climate modeling study Geophys. Res. Let. 33 L17703

[Hunt and Watkiss 2011] Hunt A and Watkiss P 2011 Climate change impacts and adaptation in cities: a review of the literature Clim. Change 104 13–49

[IPCC 2014] IPCC 2014 Climate Change 2014: Synthesis Report, Contribution of Working Groups I, II and III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change R K Pachauri and L A Meyer Core Writing Team (Geneva, Switzerland: IPCC) retrieved from https://ar5-syr.ipcc.ch/topic_futurechanges.php

[Janssen et al 2014] Janssen E, Wuebbles D J, Kunkel K E, Olsen S C and Goodman A 2014 Observational- and model-based trends and projections of extreme precipitation over the contiguous United States Earth’s Future 2 99–113

[jiang et al 2019] Jiang A, Liu X, Czarnecki E and Zhang C 2019 Hourly weather data projection due to climate change for impact assessment on building and infrastructure Sustain. Cities Soc. 50 101688

[Karimpour et al 2015] Karimpour M, Belusko M, Xing K, Boland J and Bruno F 2015 Impact of climate change on the design of energy efficient residential building envelopes Energy Build. 87 142–54

[Katz and Brown 1992] Katz R W and Brown B G 1992 Extreme events in a changing climate: variability is more important than averages Clim. Change 21 289–302

[Kirchmeier-Young et al 2016] Kirchmeier-Young M C, Lorenz D J and Vimont D J 2016 Extreme event verification for probabilistic downsampling J. Appl. Meteorol. Climatol. 55 2411–30

[Lebassi et al 2010] Lebassi B, Gonzalez J E, Fabris D and Bornstein R 2010 Impacts of climate change in degree days and energy demand in Coastal California J. Sol. Energy Eng. 132 031051–9

[Li et al 2021] Li Y, Wang W, Wang Y, Xin Y, He T and Zhao G 2021 A review of studies involving the effects of climate change on the energy consumption for building heating and cooling Int. J. Environ. Res. Public Health 18 1–18
Suckling and Stackhouse 1983 Suckling P W and Stackhouse L L 1983 Impact of climatic variability on residential electrical energy use: Environ. Res. Lett. 12 064014

Meinshausen et al 2011 Meinshausen M et al 2011 The RCP greenhouse gas concentrations and their extensions from 1765 to 2300: Clim. Change 109 213–41

Nie et al 2009 Nie L, Lindholm O, Lindholm G and Sverens E 2009 Impacts of climate change on urban drainage systems—a case study in Fredrikstad, Norway: Urban Water J. 6 323–32

NOAA 2018 NOAA 2018 Federal Climate Complex Data Documentation for Integrated Surface Data

Notaro et al 2014 Notaro M, Lorenz D, Hoving C and Schummer M 2014 Twenty-first-century projections of snowfall and winter severity across central-eastern North America: Clim. J. 27 6526–50

Petri and Caldeira 2015 Petri Y and Caldeira K 2015 Impacts of global warming on residential heating and cooling degree-days in the United States: Sci. Rep. 5 12427

Quayle and Diaz 1980 Quayle R G and Diaz H F 1980 Heating degree day data applied to residential heating consumption: J. Appl. Meteorol. 19 241–6

Rahmstorf and Coumou 2011 Rahmstorf S and Coumou D 2011 Increase of extreme events in a warming world: Proc. Natl Acad. Sci. USA 108 17965–9

Rey-Hernández et al 2018 Rey-Hernández J M, Yousif C, Gatt D, Velasco-Gómez E, San José-Alonso J and Rey-Martínez F J 2018 Modelling the long-term effect of climate change on a zero energy and carbon dioxide building through energy efficiency and renewables: Energy Build. 174 85–96

Riise and Sørensen 2013a Riise R and Sørensen B R 2013a The influence of oversized boilers on power efficiency, energy consumption and cost in energy flexible heat stations: I: Appl. Mech. Mater. 291–294 1816–25

Riise and Sørensen 2013b Riise R and Sørensen B R 2013b The influence of oversized boilers on power efficiency, energy consumption and cost in energy flexible heat stations: II: Appl. Mech. Mater. 291–294 1826–33

Savonis et al 2009 Savonis M J, Burkett V R, Potter J R, Kafalenos R, Hyman R and Ken L 2009 The impact of climate change on transportation in the Gulf Coast: TCLEE 2009: Lifeline Earthquake Engineering in a Multihazard Environment vol 357

Schaeffer et al 2005 Schaeffer M, Selten F M and Opsteegh J D 2005 Shifts of means are not a proxy for changes in extreme winter temperatures in climate projections: Clim. Dyn. 25 51–63

Scoccimarro et al 2011 Scoccimarro E, Gualdi S, Bellucci A, Sanna A, Fogli P G, Manzini E, Vichi M, Oddo P and Navarra A 2011 Effects of tropical cyclones on ocean heat transport in a high-resolution coupled general circulation model: J. Clim. 24 4368–84

Sekhar et al 2018 Sekhar C, Anand P, Schiavon S, Tham K W, Cheong D and Saber E M 2018 Adaptable cooling coil performance during part loads in the tropics: A computational evaluation: Energy Build. 159 148–63

Semenov 2007 Semenov M A 2007 Development of high-resolution UKCIP02-based climate change scenarios in the UK: Agric. For. Meteorol. 144 127–38

Semenov and Stratonovich 2010 Semenov M and Stratonovich P 2010 Use of multi-model ensembles from global climate models for assessment of climate change impacts: Clim. Res. 41 1–14

Shen 2017 Shen P 2017 Impacts of climate change on U.S. building energy use by using downscaled hourly future weather data: Energy Build. 134 61–70

Sillmann et al 2013 Sillmann J, Kharin V V, Zhang X, Zwiers F W and Bronaugh D 2013 Climate extremes indices in the CMIP5 multimodel ensemble: I. Model evaluation in the present climate: J. Geophys. Res. Atmos. 118 1716–33

Sillmann et al 2017 Sillmann J et al 2017 Understanding, modeling and predicting weather and climate extremes: challenges and opportunities: Weather Clim. Extrem. 18 65–74

Sivak 2013 Sivak M 2013 Air conditioning versus heating: climate control is more energy demanding in Minneapolis than in Miami: Environ. Res. Lett. 8 014050

Stewart and Deng 2015 Stewart M G and Deng X 2015 Climate impact risks and climate adaptation engineering for built infrastructure: ASCE-ASME J. Risk Uncertain. Eng. Syst. A 1 04014001

Suckling and Stackhouse 1983 Suckling P W and Stackhouse L L 1983 Impact of climatic variability on residential electrical energy consumption in the Eastern United States: Arch. Meteorol. Geophys. Bioclimatol. A 33 219–27

Taylor et al 2012 Taylor K E, Stouffer R J and Meehl G A 2012 An overview of CMIP5 and the experiment design: Bull. Am. Meteorol. Soc. 93 485–98

Timmer and Lamb 2007 Timmer R P and Lamb P J 2007 Relations between temperature and residential natural gas consumption in the Central and Eastern United States: J. Appl. Meteorol. Climatol. 46 1993–2013

Ürge-Vorsatz et al 2014 Ürge-Vorsatz D et al 2014 Buildings Climate Change 2014: Mitigation of Climate Change: Contribution of Working Group III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change: O Edenhofer et al (Cambridge Cambridge University Press)

Vano et al 2020 Vano J et al 2020 Comparing downscaled LOCA and BCSD CMIP5 Climate and Hydrology Projections—Release of downscaled LOCA CMIP5 Hydrology vol 96 retrieved from: https://gdo-dcp.ucllrdn.org/downscaled_cmp_projections/technoLoca/BCSD_Hydrology_tech_memo.pdf

Vichi et al 2011 Vichi M et al 2011 Global and regional ocean carbon uptake and climate change: sensitivity to a substantial mitigation scenario: Clim. Dyn. 37 1929–47

Voldoire et al 2013 Voldoire A et al 2013 The CNRM-CM5.1 global climate model: description and basic evaluation: Clim. Dyn. 40 2091–121
Volodin E M, Dianskii N A and Gusev A V 2010 Simulating present-day climate with the INMCM4.0 coupled model of the atmospheric and oceanic general circulations Izv. Atmos. Ocean. Phys. 46 414–31

Vose R S, Easterling D R, Kunkel K E, LeGrande A N and Wehner M F 2017 Temperature changes in the United States. In: Climate Science Special Report: Fourth National Climate Assessment, Volume I, ed D J Wuebbles, D W Fahey, K A Hibbard, D J Dokken, B C Stewart and T K Maycock U.S. Global Change Research Program, Washington, DC, USA. 185–206

van Vuuren D P et al 2011 The representative concentration pathways: an overview Clim. Change 109 5–31

Wang and Chen Q 2014 Impact of climate change heating and cooling energy use in buildings in the United States Energy Build. 82 428–36

Watanabe M et al 2010 Improved climate simulation by MIROC5: mean states, variability, and climate sensitivity J. Clim. 23 6312–35

Watanabe S et al 2011 MIROC-ESM: model description and basic results of CMIP5-20c3m experiments Geosci. Model Dev. Discuss. 4 1063–128

Wu S, Markus M, Lorenz D, Angel J R and Grady K 2019 A comparative analysis of the historical accuracy of the point precipitation frequency estimates of four data sets and their projections for the Northeastern United States Water 11 1279

Xu and Wang A 2019 Application of the bias correction and spatial downscaling algorithm on the temperature extremes from CMIP5 multimodel ensembles in China Earth Space Sci. 6 2508–24

Yau Y H and Pean H L 2011 The climate change impact on air conditioner system and reliability in Malaysia A review Renew. Sustain. Energy Rev. 15 4939–49

Yee T W and Stephenson A G 2007 Vector generalized linear and additive extreme value models Extremes 10 1–19

Yin J and Porporato A 2017 Diurnal cloud cycle biases in climate models Nat. Commun. 8 2269

Ylhäisi J S and Räisänen J 2014 Twenty-first century changes in daily temperature variability in CMIP3 climate models Int. J. Climatol. 34 1414–28

Yukimoto S et al 2011 Meteorological Research Institute-Earth system model version 1 (MRI-ESM1) Technical Reports vol 64 p 88

Yukimoto S et al 2012 A new global climate model of the meteorological Research Institute: MRI-GCM3—model description and basic performance. J. Meteorol. Soc. Jpn. 90A 23–64

Zhai Z J and Helman J M 2019 Implications of climate changes to building energy and design Sustain. Cities Soc. 44 511–9

IPCC 2021 Summary for Policymakers. In: Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change [Masson-Delmotte, V., P. Zhai, S.L. Connors, C. Pean, S. Berger, N. Caud, Y. Chen, L. Goldfarb, M.I. Gomis, M. Huang, K. Leitzell, E. Lonnoy, J.B.R. Matthews, T.K. Maycock, T. Waterfall, O. Yelecki, R. Yu, and B. Zhou (eds.)]. Cambridge University Press, Cambridge, United Kingdom and NewYork, NY, USA, pp. 3–32,