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# Model-Based Extreme Weather Data for Predicting the Performance of Buildings Entirely Conditioned by Ambient Energy

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*This study reports the development of extreme meteorological year (XMY) data for simulating buildings that are heated and cooled entirely by ambient energy in four climates varying in outdoor temperature and cloudiness. Electrification of conventional buildings is insufficient to meet climate goals since nearly half of U.S. electricity will still be produced from fossil fuels by 2050. Ambient-conditioned buildings depend on non-fossil sources such as the sun for heating and nighttime air or sky radiation for cooling. Such buildings are more susceptible to weather variability than conventional buildings, which simply use more auxiliary energy whenever weather conditions are challenging. On the other hand, ambient-conditioned buildings are more resilient to power outages so long as the design accounts for unusual weather during extreme years to consistently maintain indoor comfort. Ambient-conditioned buildings designed to remain comfortable with typical meteorological year (TMY2020) data produced up to over 1000 h per year of uncomfortable indoor temperature during the years (1998–2020) from which the TMY was derived. Parameters related to outdoor air temperature, sky temperature, and insolation were found to be unreliable for identifying the most challenging years. Rather, a whole-building model allowed the identification of the two most challenging years for heating and cooling, respectively. An XMY file concatenated from the most challenging summer and the most challenging winter provided a good match of indoor temperature predictions to those from the full individual years. This new XMY file facilitates the design of ambient-conditioned buildings for reliable indoor comfort.* [DOI: 10.1115/1.4065155]

*Keywords: typical meteorological year, extreme meteorological year, passive solar, passive cooling, ambient energy, buildings, simulation, thermal comfort, ventilation*

## Introduction

Buildings are responsible for nearly half of U.S. energy use and 42% of global carbon emissions [1]. The problem will grow in the future since built floor area is expected to double by 2060 [2]. Electrification of conventional buildings will not sufficiently reduce emissions because 44% of electricity will still be produced by fossil fuels by 2050 [3]. Buildings conditioned by ambient energy (from the sun, air, ground, and sky) represent a cleaner alternative. Resilience to power disruptions is also emerging as a concern as storms become more severe. Ambient buildings are inherently more resilient since they use ambient energy for space conditioning rather than electricity. Examples of buildings that are entirely or nearly entirely conditioned by ambient energy include Maria Telkes' 1948 Dover, MA house, Harold Hay's 1973 Atascadero, CA house, Paul Shippee's 1978 Longmont, CO house, Norm Saunders' 1981 Shrewsbury, MA house, Jim Riggins' 2011 Monument, CO house, and the author's 2021 Pagosa Springs, CO house [4].

While Telkes studied 65 years of weather data to design the solar heating system for her Dover house [5], the predominant current practice for both conventional and ambient-conditioned buildings is to utilize a single typical meteorological year (TMY) of weather data that are concatenated from decades of real data to represent a mean or median of weather conditions for the period from which it is derived. TMY data work well to predict typical heating and cooling loads for conventional buildings [6–8], for which mechanical conditioning equipment is sized with an ad hoc safety factor to accommodate extreme weather.

Extreme meteorological year (XMY) weather data have been proposed to more quantitatively determine the oversizing of equipment needed to maintain consistent indoor comfort throughout the most challenging periods of weather [6–8]. Comfort is maintained in extreme weather in conventional buildings simply by using more auxiliary energy that is treated as being essentially unlimited. For buildings conditioned exclusively by ambient sources, the need for XMY data is more critical because limited ambient energy during extreme weather directly impacts indoor comfort. Analogous to the oversizing of conventional heat and cooling equipment, thermal capacitance inside the building must be increased to

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bridge intervals of unavailability of the appropriate ambient sources of energy.

Crawley and Lawrie [6] cautioned that ambient-conditioned buildings may require typical and extreme weather data sets assembled based on parameters different from those of conventional buildings. Indeed, TMY and XMY that work well for conventional buildings did not accurately represent the mean/median nor extreme performance of an ambient-conditioned building in an initial study of one (heating-dominated) climate [9]. In this initial study, the simulated indoor temperature in a house designed with TMY2020 (derived from real data from 1998 through 2020) dropped below the chosen comfort range (20–25 °C) for 16 of 23 years. XMY for conventional buildings did not perform significantly better. The maximum interval during which the 24-h average solar load ratio remains below 1 was found to be a promising index for identifying the year most challenging in terms of heating performance.

The current study will expand on the previous one by investigating the suitability of TMY data for predicting the performance of ambient-conditioned buildings in four climates—Madison, WI (cold and cloudy), Rock Springs, WY (cold and sunny), Miami, FL (hot and cloudy), and Phoenix, AZ (hot and sunny). The indoor temperature will be predicted for all years 1998–2020 for a building designed to remain comfortable with TMY2020 data. The increase or decrease in thermal time constant for the building required to marginally maintain comfort in each year of real data will also be determined.

A single year is obviously preferable to decades of simulation to ensure reliable indoor comfort. Weather parameters will be evaluated for their correlation with the required time constant as a means of identifying extreme years. Finally, building performance will be simulated for a single year of XMY data concatenated from the most challenging winter (for heating) and the most challenging summer (for cooling) and compared to results from the two complete years.

## Methods

Each home was simulated using a single thermal zone, first-order model [10]. The model calculates hourly indoor temperature with no auxiliary heating or cooling. For nighttime ventilation cooling, which was used for the two cold climates

$$mc_p \frac{\partial T}{\partial t} = F_s S A_c + G - UA(T - T_a) - F_v h A_v (T - T_a) \tag{1}$$

where $m$ is thermal mass, $c_p$ is its specific heat, $T$ is indoor temperature, $t$ is time, $F_s$ and $F_v$ are control functions (0 or 1) for solar gains and ventilation cooling, $S$ is absorbed solar gain, $A_c$ is solar aperture area, $G$ is internal heat gain, $UA$ is the building envelope loss rate, $T_a$ is ambient temperature, and $hA_v$ is the ventilation cooling coefficient. Model-based control of solar gains (shading) and nighttime ventilation cooling is included in the model. See Ref. [10] for other details.

For sky cooling, which was used for the two hot climates, the model becomes [11]

$$mc_p \frac{\partial T}{\partial t} = F_s S A_c + G - UA(T - T_a) - F_r A_r \sigma \epsilon (T^4 - T_s^4) \tag{2}$$

where $F_r$ is the control function (0 or 1) for sky cooling, $A_r$ is radiator area, σ is the Stefan–Boltzmann constant, $\epsilon$ is the effective radiator emittance, and $T_s$ is sky temperature. To represent practical radiators, the emittance is taken as 0.7, but for simplicity, the radiator losses/gains to ambient are neglected. Because of the quartic Eq. (2), the solution is a bit more complicated than for Eq. (1) but can still be done analytically.

Similitude for the ventilation cooling model will be described as an example. Normalizing Eq. (1) by $(UA + F_v h A_v)\Delta T_0$, where $\Delta T_0$ is the difference between baseline indoor temperature $T_b$ (18.3 °C) and the extreme outdoor temperature $T_O$ (the annual minimum for a heating-dominated climate), shows that consistent with the Buckingham Pi theorem, the dimensional Eq. (1) with five parameters can be reduced to a dimensionless equation with just two parameters

$$\frac{\tau}{1 + F_v VLR} \frac{\Delta T_o}{\Delta T_c} \frac{\partial (T/\Delta T_o)}{\partial (t/\Delta t_o)} = \frac{F_s SLR + ILR}{1 + F_v VLR} - \frac{T - T_a}{\Delta T_o} \tag{3}$$

where the solar load ratio is $SLR = SA_c/UA\Delta T_o$, the internal heat generation load ratio is $ILR = G/UA\Delta T_o$, the ventilation cooling load ratio is $VLR = hA_v/UA$, and the nondimensional thermal time constant is $\tau = mc_p \Delta T_c / UA \Delta T_o \Delta t_o$, where $\Delta t_o$ is the maximum period of cloudy weather during which solar gains are insufficient for heating (for a heating-dominated climate). (Including the temperature ratio $\Delta T_c/\Delta T_o$ reduces the time constant, making it more representative of the length of time that the building can remain comfortable without significant solar gains when the outdoor temperature is the coldest.) The two parameters $\frac{\tau}{1 + F_v VLR} \frac{\Delta T_o}{\Delta T_c}$ and $\frac{F_s SLR + ILR}{1 + F_v VLR}$ fully define the solution, but in this case, they are left in the form of the more primitive load ratios to show the dependence of the parameters on weather, building design, and occupancy patterns.

TMY2020 weather data (concatenated from the years 1998–2020 with weighting on outdoor dry bulb and wet bulb temperatures, wind speed, and direct normal insolation (DNI) [12]) were used as the baseline. TDY2020 (weighted entirely on DNI) and TGY2020 (weighted entirely on total horizontal insolation (GHI)) were also evaluated. Each individual year from 1998 to 2020 was also simulated with the baseline values. With all other building characteristics held constant, the thermal capacitance required to marginally maintain comfort for each individual year was also determined.

Iterations were used to match the initial and final indoor temperatures for each year of simulation. (This procedure is typical for periodic solutions, which is only approximately the case for weather data. Nonetheless, this protocol allows performance for each year to be evaluated independent of previous weather.) The final temperature for the first year of simulations was used as the initial temperature for a second year of simulations with the same weather data, which, in each case, produced the same final temperature.

In each climate, the peak envelope loss or gain (for heating- and cooling-dominated climates, respectively) was set to the Passivhaus standard of 10 W/m$^2$. Internal heat generation was set to a representative value of 4.05 W/m$^2$. The ratio of south-facing solar aperture to floor area was set to 0.05 for Miami and Phoenix. For sufficient winter solar gains, Madison and Rock Springs required ratios of 0.07 and 0.1, respectively. The ventilation cooling load ratio VLR was set to 29 and 19 for Madison and Rock Springs, respectively. Sky cooling with a radiator area equal to half the floor area was used in Miami and Phoenix. Thermal capacitance to marginally maintain the comfort limits of 20 °C–25 °C for TMY2020 weather was 315, 264, 233, and 1247 kJ/m$^2$ K for Madison, Rock Springs, Miami, and Phoenix, respectively. (These values can be compared to the range of light to heavy conventional construction from 125 to 452 [10]). The dimensional thermal time constants $\tau\Delta t_o = mc_p \Delta T_c / UA \Delta T_o$ become 1.69, 1.49, 0.73, and 1.60 days. The transmittance/absorbance product for solar gains was set to 0.5.

## Results

Simulated annual temperature ranges are shown in Fig. 1. In Madison, the house designed to maintain comfort in TMY weather remains consistently comfortable for only three of the 23 individual years. The house overheats for 6 years, undercools for TDY, TGY, and 18 individual years, including 4 years when it both overheats and undercools (Fig. 1). In Rock Springs, the TMY house maintains comfort for four of the individual years, but overheats for 2018 and undercools for TGY and for 18 individual years.

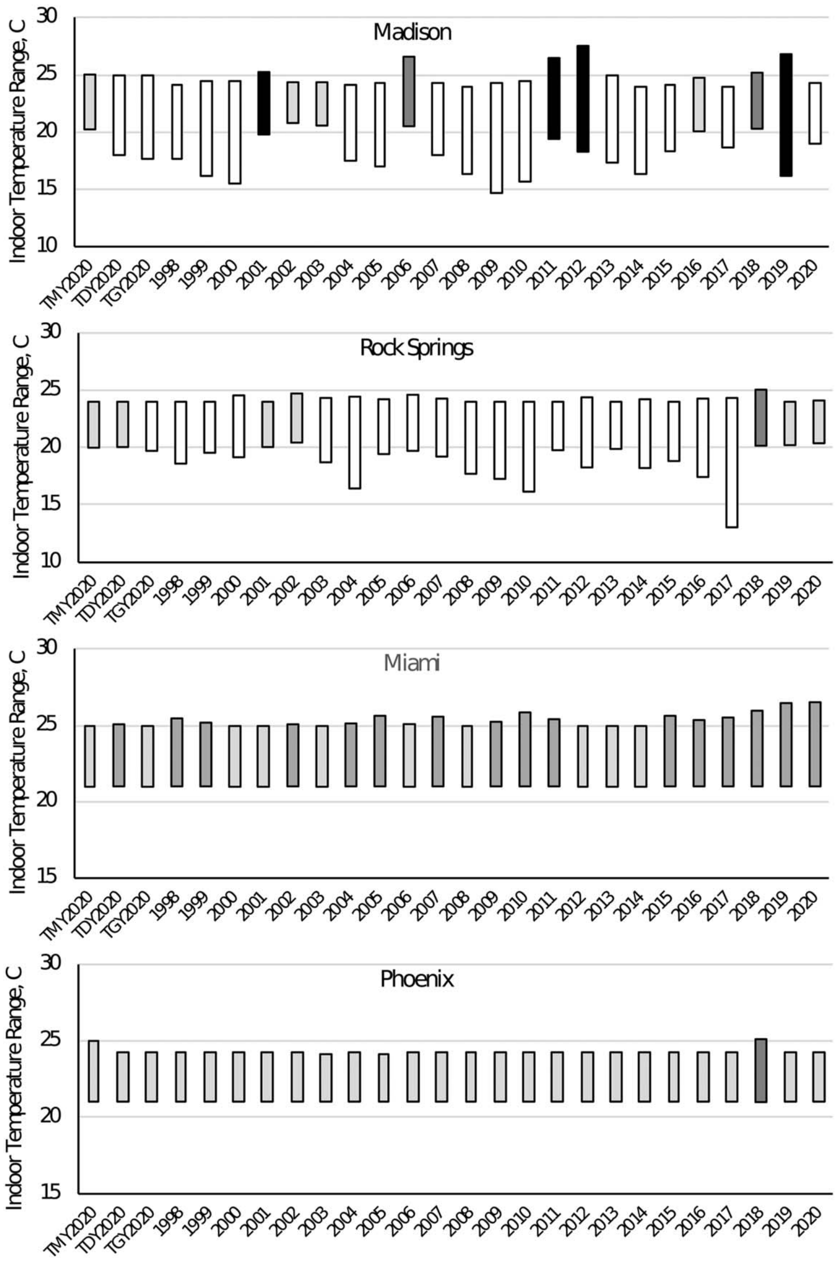


**Fig. 1 Annual indoor temperature range compared to the comfort range of 20–25 °C (light gray: comfort maintained year round; white: undercooling; dark gray: overheating; black: undercooling and underheating)**

In Miami, the TMY house overheats for TDY and for 15 of the 23 individual years. No undercooling occurs for either of the hot climates. In Phoenix, the TMY house remains comfortable for TDY, TGY, and all individual years except 2018, when it overheats.

In Madison, to keep the indoor temperature within the comfort range throughout the entire period, the thermal time constant must be increased from 1.69 days for the TMY design to 7.84 days (that is required for 2009), a factor of 4.64 higher (Fig. 2). Only 2002, 2003, and 2016 required a shorter time constant. Note that 2009 produced the coldest indoor temperature for the TMY house (Fig. 1). The year 2012 produced the hottest temperature in the TMY house, but the time constant required to maintain comfort for this year is considerably lower than for 2009.

In Rock Springs, 2017 required the longest time constant, 6.65 days compared to the TMY value of 1.49 days, a factor of 4.46 higher (Fig. 2). Again, the year exhibiting the lowest indoor temperature with TMY parameters (Fig. 1) also requires the longest time constant to maintain comfort. Six of the individual years require a shorter time constant than TMY. TMY thermal capacitance produced overheating during 2018. A larger capacitance was required to maintain comfort, but the time constant based on 2018 weather is shorter. (Because the time constants for each year are based on the peak temperature difference $\Delta T_0$ for that year, there is not a direct correspondence between the time constant and thermal capacitance across different years.)

In Miami, 2020 produces the highest indoor temperature (Fig. 1), but 2019 requires a longer time constant, 14.3 days compared to 0.73 days for TMY, a factor of 19.6 higher (Fig. 2). Eight of the individual years require a shorter time constant than TMY.

In Phoenix, overheating occurs only during 2018 (Fig. 1), and this year also requires the longest time constant, 1.90 days compared to 1.60 days for TMY, a factor of only 1.19 greater (Fig. 2). All other years require a shorter time constant.

The best of several correlations of thermal time constant with weather parameters are shown in Fig. 3. Parameters tested included minimum and maximum outdoor temperature, maximum sky

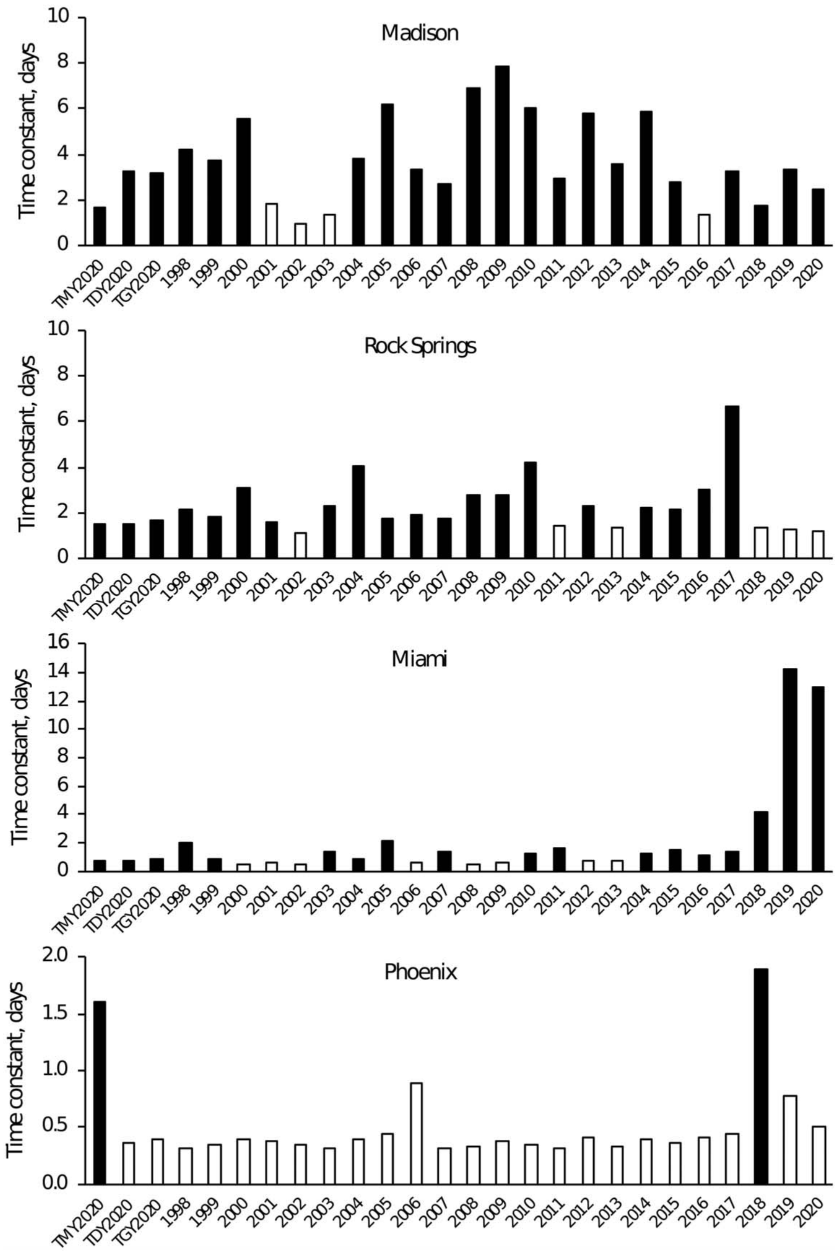


**Fig. 2 Thermal time constant required to maintain the comfort range of 20–25 °C (white: time constants shorter than TMY2020; black: time constants longer than TMY2020)**

temperature, maximum time interval with sky temperature >24 °C, maximum degree day interval with sky temperature >24 °C, heating and cooling degree days, minimum monthly average SLR, minimum 2-month (from December to February) average SLR, 3-month (December to February) average SLR, maximum time interval with 24-h average SLR < 1, maximum time interval with hourly SLR < 1, maximum time interval with GHI < 300 W/m$^2$, maximum degree day interval with GHI < 300 W/m$^2$, maximum time interval with DNI < 100 W/m$^2$, and maximum degree day interval with 24-h average DNI < 100 W/m$^2$.

For Madison, the best correlation is with the maximum degree day interval with GHI < 300 W/m$^2$ (Fig. 3). The longest interval occurs for 2009, which also requires the longest time constant (Fig. 2) and exhibits the lowest indoor temperature with TMY parameters (Fig. 1). However, the coefficient of determination $R^2 = 0.509$ is not good. TMY, TDY, and TGY all appear on the left of the curve at low intervals.

For Rock Springs, the best correlation is with the minimum monthly average SLR (Fig. 3). The lowest SLR occurs for 2017, which also requires the longest time constant and exhibits the lowest indoor temperature (Fig. 1). The coefficient of determination $R^2 = 0.798$ is reasonably good. TMY has a moderate SLR compared to the individual years, but TDY and TGY have relatively high SLR.

For Miami, the best correlation is with cooling degree days (Fig. 3). The years 2019 and 2020 have many more degree days than the other individual years, need the longest time constants, and produce the greatest overheating with TMY parameters (Fig. 1). The coefficient of determination $R^2 = 0.707$ is reasonable largely because 2019 and 2020 are such outliers. The years 2015 and 2018 were also warm, but 2015 did not require a significantly longer time constant than the cooler years. TMY, TDY, and TGY all have relatively low heating degree days and require short time constants.

For Phoenix, the best correlation is with the maximum time interval of sky temperature >24 °C (Fig. 3), but the coefficient of

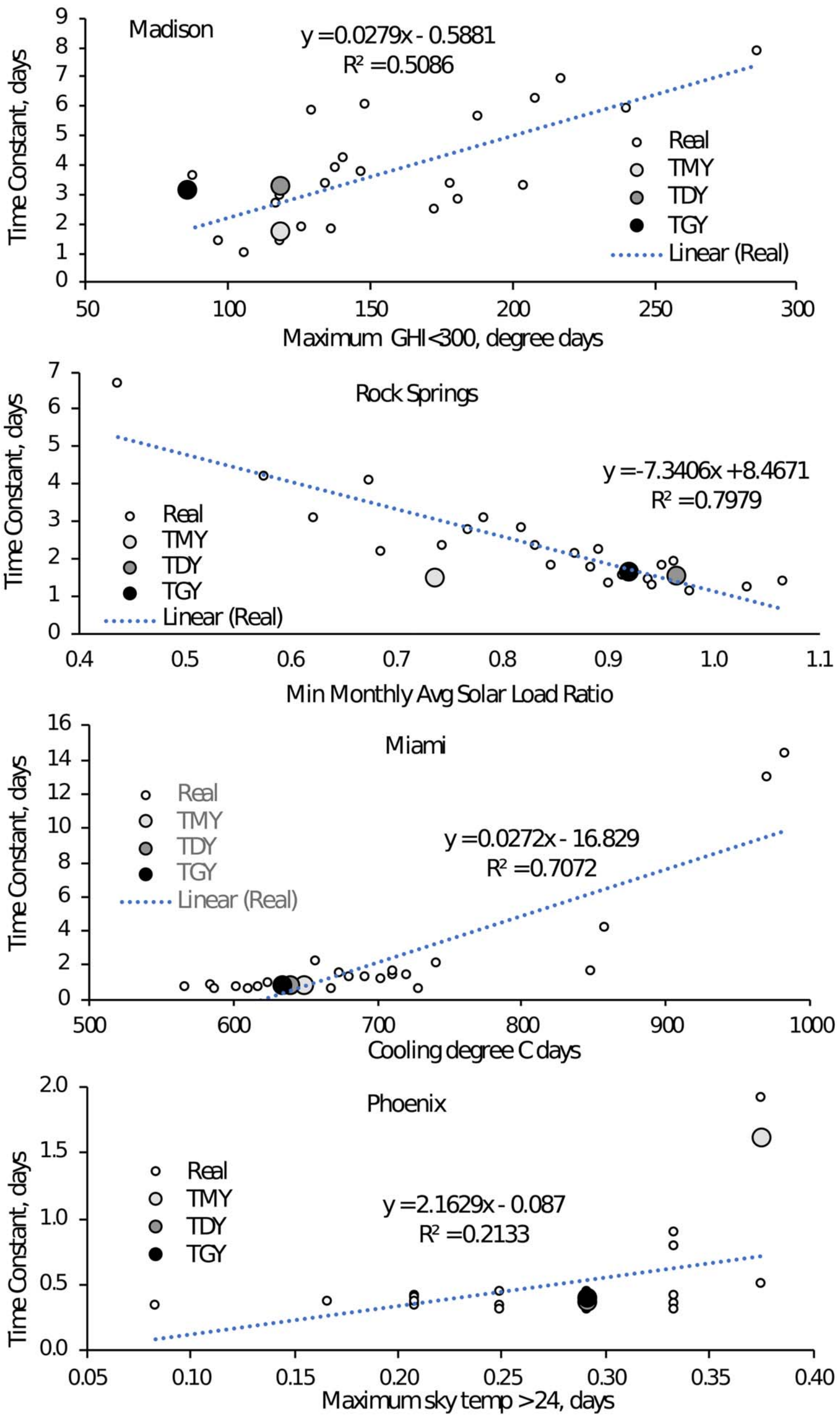


**Fig. 3 Correlation of thermal time constant with weather parameters**

determination $R^2 = 0.213$ is not good. All of the intervals are less than 1 day, reflecting that Phoenix has sky cooling potential every night. The year 2018 and TMY require long time constants compared to the other real and typical years; 2018 is also the only year with overheating with TMY parameters (Fig. 1).

Histograms of indoor temperature are shown in Fig. 4, with the axis values being the upper limit of temperature bins (e.g., the 25 °C bin is from 24–25 °C). In each location, shown are the typical years and the individual years with the most undercooling and the most overheating, as well as a year concatenated from the winter with the greatest undercooling and the summer with the greatest overheating. (Summer is taken as Julian hours 3000–7000 and winter the remainder of the year. These intervals match those for seasonal control functions [10,11]). The 21–24 °C bins are truncated so that the lower and higher temperature bins can be seen in more detail.

For Madison, 2009 has 1171 h of undercooling in the 15–20 °C temperature bins but only 162 h in the 15–16 °C bins (Fig. 4). These amount to 13.4% and 1.8% of the year, respectively. The year 2012 produced 155 h of overheating in the 26–28 °C temperature bins, for 1.8% of the year. TGY undercools to the 16 °C bin, and TDY undercools to the 17 °C bin, but both overheat just 1 h in the 26 °C bin. The extreme year concatenated with winter from 2009 and summer from 2012 reproduces perfectly the hours of undercooling and overheating during 2009 and 2012, respectively.

For Rock Springs, 2017 produces 826 h of undercooling in the 14–19 °C bins but only 196 in the 14–16 °C bins (Fig. 4), for 9.4% and 2.2% of the year, respectively. The year 2007 is the

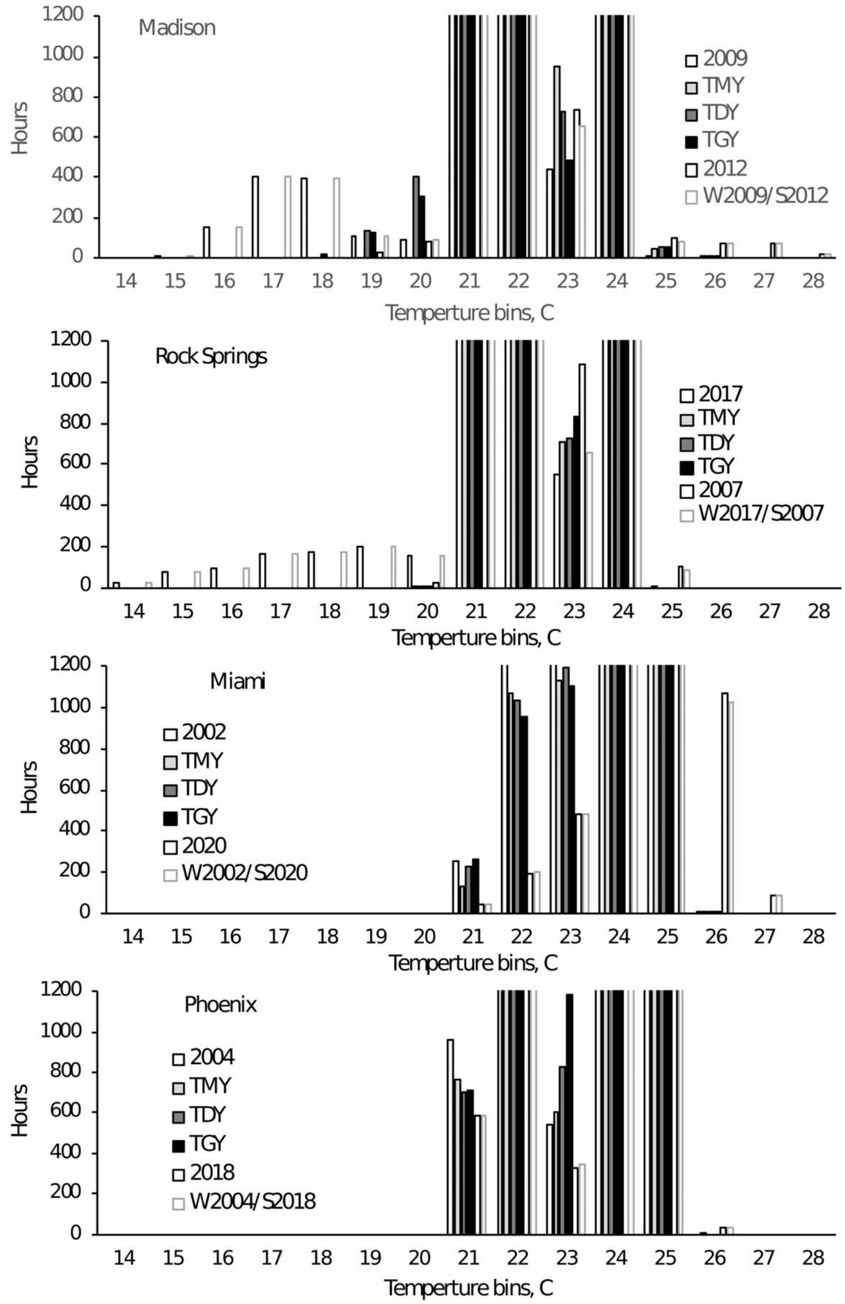


**Fig. 4 Histograms of indoor temperature (white: year with the most undercooling; dark pattern: year with the most overheating; light pattern: a year concatenated from the winter with the most undercooling and the summer with the most overheating)**

hottest, but it does not overheat beyond the 25 °C bin. None of the typical years undercool or overheat beyond the 20–25 °C bins. The concatenated extreme year reproduces these hours of undercooling during 2017 exactly.

For Miami, no undercooling occurs, though the coldest year 2002 exhibits more hours in the lowest temperature bins within the comfort range (Fig. 4); 2020 produces 1070 h of overheating in the 26 °C bin and 87 h in the 27 °C bin for 12.2% and 0.99% of the year, respectively. The concatenated extreme year produces considerably fewer hours in the low comfort temperature bins but reproduces the overheating closely, with 1030 h in the 26 °C bin and 87 h in the 27 °C bin.

For Phoenix, 2004 produces more hours in the lowest comfort temperature bins but no undercooling (Fig. 4). The year 2018 exhibits 32 h of overheating in the 26 °C bin, 0.37% of the year. The concatenated extreme year produces fewer hours in the lowest comfort temperature bins than 2004 but matches the overheating of 2018 exactly.

## Discussion

In Phoenix, the building designed with TMY data maintains comfort for every year from 1998 to 2020, except for 2018, which overheats by only 0.1 °C for 32 h, which is 0.37% of a single year and 0.016% of the full 23-year period. This small deviation from the comfort range and its short duration would probably be acceptable to most occupants and may be unnoticed by many. However, the buildings in other climates experience more substantial excursions from the comfort range for longer periods, with Rock

Springs undercooling for a total of 826 h in 2017 and by as much as 6 °C (for 22 h).

Completely eliminating undercooling and overheating is possible but may require a substantial increase in thermal time constant, for instance, up to about 20 times more in Miami (Fig. 2) to reduce overheating by 2 °C (Fig. 4). In comparison, a smaller 4 times greater time constant reduces undercooling by a larger 6 °C in Rock Springs. Such oversizing of the time constant is more than the safety factor typically applied to conventional heating and cooling equipment (about 2.3) and may be a reason for the unexpectedly poor performance of some passive solar buildings in the past.

The perception of comfort varies among individuals, as does the importance of deviations from a chosen comfort range [13]. By performing the multi-year simulations such as in this paper, a choice is available for each building in each location between the expense of the added thermal mass and the marginal increase in performance.

A similar choice is available for the establishment of broader performance standards, whether for architectural and construction firms or for rating agencies. For example, Passivhaus certification allows buildings to overheat (above 25 °C) for up to 10% of the year, every year, by an unspecified temperature difference [14]. This standard could be met, for instance, by a house that overheats for 9 h every day during 3 months of summer. Some occupants may find this level of performance acceptable but others not. It is beyond the scope of this paper to develop a new standard. Such a market-based study would be a good topic for future research. The results of this paper facilitate the refinement of standards based on the frequency and magnitude of undercooling and overheating events predicted from decades of weather data.

To simplify the simulation of ambient-conditioned buildings, the identification of the most challenging years by analyzing weather parameters alone was found to be problematic. While the highest or lowest values of the weather parameters in Fig. 3 correspond with the longest time constant required to maintain comfort, the correlations across all years are generally poor, and the best correlation is with a different parameter in each location. A more thorough evaluation of parameters might yield better results. However, a more reliable alternative seems to be performing multi-year simulations with the whole-building model (Eqs. (1) and (2)), as was done in this study. Such simulations, if automated, would be fast and may take no more time than an extensive comparison among weather parameters.

These results suggest that the two most challenging years for heating and cooling can be consolidated into a single XMY file for simulating performance during both seasons of extreme weather. Indoor temperature simulated with this XMY file followed closely the performance during the full, individual extreme years (Fig. 4). Such response can be expected to prevail so long as the thermal time constant is much shorter than the length of the seasons.

While not rigorously confirmed, the principles of similitude suggest that for the same weather data, identical building performance should be obtained for other values of the load ratios (SLR, ILR, and VLR) so long as the two Buckingham Pi parameters in Eq. (3) remain the same. Such a result could reduce the computational effort of studying variations in building design.

**Limitations.** Limitations of this study include the following: (1) This study includes only four locations. Therefore, a new XMY file must be developed for each new location. A database, such as the National Solar Radiation Data Base (NSRDB), could calculate and archive these files along with TMY, TDY and TGY files. (2) The models of Eqs. (1) and (2) are purposefully simple to streamline inputs and reduce computational effort, as is appropriate for a predesign tool intended to establish performance targets before detailed design is initiated. More comprehensive models may be advisable for the final design. (3) This study uses archived weather data. Building design should ideally be performed with future meteorological year (FMY) data based on predicted climate change over its expected lifetime. A publicly available design tool for ambient-conditioned buildings featuring extreme FMY data sets would be valuable.

## Conclusions

This expanded study again confirms the speculation of Ref. [6] that TMY weather data are unreliable for simulating the typical performance of a building conditioned with ambient energy. Extreme years can lead to significantly different building performance for a building designed with TMY data and require considerably different building characteristics (thermal time constant in this study) to maintain indoor temperature within a chosen comfort range. As such, simulation during extreme years is needed to fully characterize the range of predicted performance of the building.

In this study, weather parameters alone were inconsistent for identifying extreme years. However, multi-year simulations with the whole-building model in these four locations reliably established the most challenging years for heating and cooling. Based on the four different climates in this study, the extreme summer and winter seasons from these two most challenging years can be concatenated into a single XMY data set for simulating ambient-conditioned buildings in the same climate. Using this new XMY data set facilitates consistent indoor comfort throughout every year from which the XMY is derived.

## Conflict of Interest

There are no conflicts of interest.

## Data Availability Statement

The datasets generated and supporting the findings of this article are obtainable from the corresponding author upon reasonable request.

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