Bounding long-term building energy performance with single-year extreme weather files

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Abstract

The representation of typical weather conditions is well understood, but the resilient design and operation of buildings is influenced by extremes. Here, we advance the proposal of eXtreme Meteorological Years (XMYs), first introduced by Crawley & Lawrie in 2015, bounding the peak building energy performance for space heating and cooling with a single, composite year.

Past XMYs formulations have been shown to work for several climates, but not all, and this work seeks to address this while improving XMYs performance. The novel quantile approach based on degree days shows that XMYs can bound energy performance within ±5 $kWh \cdot m^{-2} \cdot a^{-1}$. These results demonstrate XMYs can reliably bound performance to a degree compatible with decision-making for building design and operations.

Key Innovations

- Devised a new approach for XMYs research and development.
- Established XMYs performance expectations given variability in the response of the building stock to weather.
- Proved the feasibility of the XMYs concept to bound peak annual energy demands in a single weather file.
- Developed a new formulation for XMYs that overcomes past barriers of applicability across climate zones in ANSI/ASHRAE Standard 169-2021.

Practical Implications

We advanced the XMY concept that bounds the multi-year performance of buildings' heating and cooling energy demand in a single-year composite weather file. Capturing extremes allows appraising resilience, and doing so in this way removes barriers to practical applications as it is compatible with established workflows built on single-year composite weather files like TMYs, which are commonplace worldwide.

Introduction

A decarbonized built environment is key to climate change mitigation and adaptation, yet buildings still consume 29% of the global primary energy, mainly due to space conditioning demand. As the climate changes, there is a need to closely and rigorously map the boundary conditions of buildings to facilitate learning from typical and atypical weather events (Crawley and Lawrie 2021).

The representation of typical weather conditions is well understood, but resilient design and operation of buildings is also influenced by responses to extremes (Herrera et al. 2017). This could be assessed through multi-year weather files, but such an approach is computationally intensive and onerous for conceptual design. Another approach is the consideration of extreme weeks, since it provides a familiar reference frame to visualize the impacts of a heating climate (Coley, Liu, and Fosas 2022, Ramallo-González et al. 2020). However, established practices favor year-long appraisals of performance that are directly compatible with existing workflows in building energy modelling (Herrera et al. 2017, Rostami, Green-Mignacca, and Bucking 2024). Hence, this work advances the proposal of eXtreme Meteorological Years (XMYs), weather files that bound the building energy performance for space heating and cooling with a single, composite year.

The representation of climatic data for building performance simulation as XMYs was first introduced by Crawley & Lawrie (2015). Conceptually, XMYs build on the well-established approach of Typical Meteorological Years (TMY), which successfully represent prevailing meteorological conditions present over long periods using a single, composite-year weather file. However, XMYs purposely select more extreme weather periods (e.g., months, seasons) to bound the performance present in the same multi-year period of record on which they are based.

Past methods for creating XMYs were proposed by Crawley and Lawrie (2019, 2015) and Gasparella et al. (2021). Each used seasonal extremes to assemble them. These approaches work well for most locations, particularly those with significant seasonal variation throughout the year. These methods do not work well where temperatures are more constant throughout the year, such as Singapore and other tropical locations. According to the seasonal methods, the extreme months are selected to maximize or minimize over a 6-month period a seasonal weather variable, in this case, dry bulb temperature.

This work formalizes a research and development framework for XMYs, proves their feasibility, and derives new selection rules that can be applied to any location in the world while retaining usefulness for practical applications.

Methods

The method to create XMYs is based on high-quality, long-term weather observations that collectively characterize representative climatic conditions for building performance simulation. Multi-year weather data is then used to estimate a building's response year on year,

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which will vary accordingly to weather conditions in the absence of other variations (e.g., occupancy, building operations). Both the multi-year weather and corresponding building energy demand databases are then used to establish the feasibility of XMYs as a weather file family, and to establish user-friendly formulations that are meaningful to building energy modelling users to appraise resilience and inform building design and operations.

Weather data source

We considered a set of 36 locations (Table 1) representative of those in ANSI/ASHRAE 169-2021

Table 1: Locations (data: ANSI/ASHRAE 169-2021)

Location	Climate Zone	HDD18	CDD10
ARE - Dubai	0B	9	6,609
ARG - Buenos Aires	3A	862	3,001
AUS - Alice Springs	2B	676	4,144
BOL - La Paz	5A	3,841	41
BRA - Brasilia	2A	16	4,462
BRA - Florianopolis	2A	195	4,173
BRA - Sao Paulo	2A	206	3,914
CAN - Winnipeg	7	5,697	1,039
CAN - Resolute Bay	8	12,082	3
CAN - Toronto	5A	3,779	1,460
CHN - Shijiazhuang	4B	2,387	2,736
CHN - Hohhot	6B	4,416	1,500
CMR - Yaoundé	1A	-	5,316
DEU - Frankfurt	5A	2,854	1,379
DZA - Tamanrasset	2B	437	4,623
EGY - Cairo	2B	311	4,717
ESP - Madrid	3B	1,909	2,233
FIN - Helsinki	6A	4,637	738
GBR - London	4A	2,434	1,187
GBR - Glasgow	5A	3,352	597
GRC - Athinai	3A	1,259	2,976
IND - New Delhi	1B	284	5,749
IND - Ahmedabad	0B	10	6,580
MAR - Marrakesh	2B	600	3,937
NZL - Wellington	3A	1,759	1,430
SGP - Singapore	0A	-	6,689
TUR - Van Feritmelen	5C	3,400	1,336
TZA - Kilimanjaro	1A	1	5,158
USA - Denver	5B	3,263	1,672
USA - Atlanta	3A	1,432	3,063
USA - Honolulu	1A	-	5,664
USA - Sioux City	5A	3,716	1,782
USA - Arlington	4A	2,142	2,558
USA - Washington	4A	2,532	2,178
USA - Seattle	4C	2,567	1,193
ZAF - Cape Town	3C	848	2,637

(2021). These showcase the 10 climate zones as well as diverse geographical conditions. Using the multi-year hourly weather data series from NOAA's ISD (Smith, Lott, and Vose 2011) and solar radiation from the ERA5 reanalysis data set (Soci et al. 2024), we created individual MYs (Meteorological Years). From these individual MYs, we created typical meteorological years (TMYs) according to the technical standard EN ISO 15927-4:2005 (BS 2005). These MYs were also used in the XMYs development method described next.

XMY definition and feasibility

XMYs are based on the hypothesis that it is possible to capture in one single-year composite weather file the extreme response of buildings observed in a multi-year dataset in terms of annual energy demand – the most widely used key performance indicator in energy assessments. Further, there is interest in capturing both heating and cooling extremes. Owing to the diversity of the building stock worldwide and their end-uses, it is recognized that XMYs should capture *likely* extreme conditions. XMYs cannot be expected to always capture extreme responses but near-extreme responses, as different buildings in the same location can display peak energy consumption in different years, according to their design characteristics and operational strategies.

The existence of near-extreme conditions that (1) generalize to diverse buildings and (2) are close enough to extreme conditions to be useful for practical applications is explored in this work. Here, a diverse collection of reference buildings is simulated for each year of the previously established climate database. The result is a buildings' response database that is used to:

1. Evaluate the assumption that for every location, there exists a single year that displays the maximum energy consumption across all buildings. This entails querying the database to obtain the years at which building responses peaked and to check whether these remain the same for all buildings when grouped by location. As argued, this is a test that is expected to fail, but the fraction of locations where this condition is satisfied provides meaningful context to gauge XMY performance expectations.
2. Evaluate the assumption that there is a common set of year(s) across all building types for the nth greatest energy use. This requires finding the common year across all building types in the same location where energy consumption is the highest. This value for energy consumption can then be compared with the peak one for each building type to establish expected absolute ($kWh \cdot m^{-2} \cdot a^{-1}$) and relative tolerances (percentage and percentile).

Collectively, these tests establish ahead of time the feasibility of the XMY concept: what would be the optimal performance expectations, and whether such expectations are compatible with meaningful building energy performance assessments in practice.

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Figure 1: Flexible definition of heating and cooling seasons across samples in all ASHRAE 169-2021 climate zones: proportion of HDD and CDD per month (red: HDD relative influence, blue: CDD ones)

XMY creation

Weather file creation strategies need to be generalizable to diverse building stocks, not just one building type. This leads to the idea that, for weather files type formulations to be useful, they need to be solely dependent on weather information (and by extension, climate). Otherwise, there is no advantage to having a single-year weather file type because modelers would, in such a scenario, have to undertake simulations across all available years. Given that overall weather-related energy use of buildings is primarily determined by space conditioning, we first turn to Heating and Cooling Degree Days (HDD and CDD, respectively) as well-established proxies for building energy use in the literature (ASHRAE 2021, CIBSE 2006). It has been demonstrated in the context of TMYs and auxiliary analyses conducted as part of this work that other weather variables, like solar radiation or wind speed, only contribute to a small fraction of the variability in energy performance results.[1]

Climate data shows that there exist all possible combinations of buildings with/without heating/cooling requirements. Having locations solely dominated by heating or cooling requirements and options in between means that overall energy consumption may be dominated by space heating alone, space cooling alone, or a combination of both.[2] This gives rise to the well-established notion of seasonality, but in the context of XMY work, and contrary to past approaches, a *flexible* definition of heating and cooling seasons across locations in the world is needed. XMYs are required to be composite years like other types of weather files, such as TMYs. Informed by previous work on XMYs, this one assumes that monthly intervals will provide enough resolution to capture seasonality and to establish the existence of XMYs. The basis for selecting each month in the composite year is linked to heating and/or cooling requirements and must approximate observed extreme annual energy demand in the multi-year building performance database.

Here, a simple formulation for heating and cooling seasons is established through HDD and CDD as continuous periods in a year where one or the other dominates (Figure 1, baseline temperatures for both are 18°C). XMY creation will be allowed to make use of this information for the routine that selects months in the multi-year weather database. It is important to consider that performance is established in *annual* energy demands (heating, cooling, total), meaning *aggregated over the full composite year*. The reason is that there are locations where monthly metrics for HDD and CDD show significant contributions to both, and there is an ambition to have a simple, intuitive formulation of XMYs.

Having established initial conditions that enable the definition of XMYs, the next step is to define the algorithm that selects months in the multi-year weather database to create the composite year. There is no single way to explore this, and this work opted for a first-principles, simple formulation (recipe) based on educated estimates that bound the performance of XMY candidates. This favored a quantile-based XMY recipe:

1. If months with the *highest* HDD/CDD (as informed by the flexible season definition) are selected across all months in the relevant season, the resulting XMY will deliver an energy demand well above the

[1] Owing to space constraints, auxiliary analyses are not included, please see report on TMYs for an in-depth overview and discussion (Wilcox and Marion 2008).

[2] In a way, locations that do not require heating nor cooling are not in scope for XMYs since energy performance would be expected to be uncorrelated to weather conditions. If they were, such buildings would represent a small proportion across the building stock of interest and would warrant bespoke explorations of performance.

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maximum on record in the building performance database. The reason is that it is highly unlikely that the year with the peak space heating/cooling demand includes the most extreme months on record for the entire heating/cooling season. Hence, a quantile of 100 is considered a theoretical upper bound.

2. If months with the *lowest* HDD/CDD (as informed by the flexible season definition) are selected across all months in the relevant season, the resulting XMY will deliver an energy demand that is well below the minimum on record in the building performance database. Hence, a quantile of 0 is considered a theoretical low bound.
3. It follows that there must be a quantile in between these extremes that selects months that, bundled in a weather file and used in building performance simulation, approximate the peak space heating and space cooling demand of the building.

A quantile-based definition using only HDD and CDD requires a single training parameter, the quantile threshold. For simplicity, the same quantile is used for all months and both seasons. The question then becomes if such a simple approach generalizes well across all buildings in a location.

For the framework to evaluate possible formulations for XMYs, we used the building energy demand database as a lookup table. This database is built by simulating all reference building types across all years available for all locations across all climate types. Parallel to this, a lookup table was built for all location-year-month combinations with precomputed HDD and CDD. For any given XMY formulation, like the quantile-based one introduced, all that is needed is the implementation of the algorithm that builds a composite year from values precomputed in the weather lookup table. Since all possible results are precomputed in the building energy demand database, performance is approximated by selecting and aggregating precomputed results.

XMY validation

Given an XMY formulation, the validation consists of:

1. Creating an explicit EPW file that represents the XMY – one per location. In the method presented here, this is defined solely by the quantile used to choose months and the flexible heating/cooling season definition; and
2. Using said XMYs to simulate all buildings.

Although seemingly identical to the process to find suitable formulations of XMYs, this approach ensures continuity in the annual building simulation, since using lookup tables presumes the response in any given month is independent of the month preceding it (this may or may not be the case, depending on the response time of the building). By comparing these results with the first approximation, the validity of the method can be established as a way of anticipating outcomes reliably.

Analysis

The previous establishes the foundation for XMY work. At the same time, there is value in comparing the performance of XMYs against established approaches for TMYs to contrast extreme responses with expected typical ones, as well as contrasting the variability in both contexts. In particular, the following is considered of interest to frame practical applications of this work:

1. MYs: Full range of building response by considering long-term records of Meteorological Years.
2. XMYs: Building response with XMYs. This will evaluate the extent to which XMYs approximate peak energy demands obtained in the MYs set.
3. TMYs-all: Building response with TMYs built with the full set of MYs. This will evaluate the extent to which TMYs capture the average energy demand obtained in the MYs set.
4. TMYs-recent. Building response with TMYs built with the MYs records for the last 15 years. This will contextualize the effects of climate change on the average energy demand.

Reference buildings

This work uses four of the "U.S. Department of Energy Commercial Reference Building Models of the National Building Stock": Midrise Apartment, Medium Office, Small Office, and Primary School (see Deru et al. (2011) for details about model inputs and outputs across all reference building models and their relative changes).

EnergyPlus version 24.2 (2024) model variants for each location were implemented to reflect ASHRAE Standard 169-2021 climate zones and to size systems according to statistics in long-term records as per ASHRAE methods. Energy end-uses are classified from within the models using EnergyPlus "Meter" features to aggregate all relevant variables.

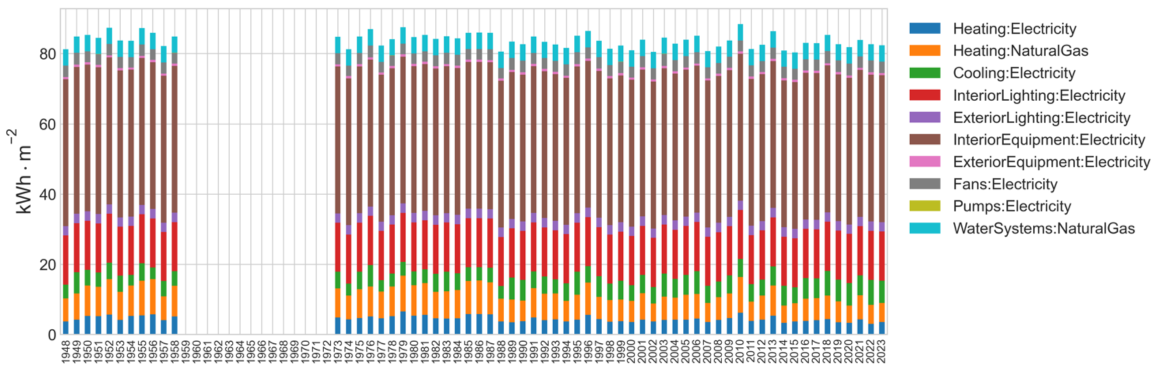

Figure 2: Example of multi-year performance - energy consumption of the Medium Office Building (London)

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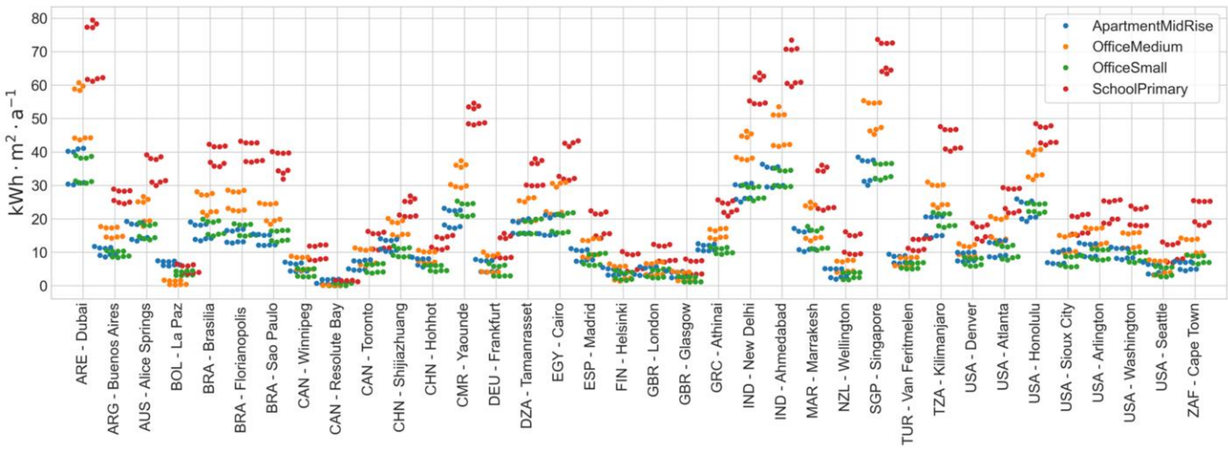

Figure 3: Overview of sampled (n=4) maximum and minimum energy demand for cooling per building type/location

Results and discussion

This section presents results and discussion together because each step influences subsequent ones. Mapping to the objectives, these are organized around the overview of building energy performance, XMY feasibility and performance, and global remarks.

Overview

The study yields 8916 cases: arising from the combination of 36 locations, 4 building types, and 62 years, on average, of weather data available for each location (the number of years per location varies according to data availability and quality). For each location-building pair, multi-year energy performance is disaggregated according to energy end-use (Figure 2), and results are stored in the building energy performance database at a monthly resolution to then establish lookup tables.

XMY feasibility

The feasibility of the XMY concept rests on the interval between minimum-maximum energy demand across years for each location-building pair, and the variability in peak energy demands. Figure 3 shows an overview of this analysis for cooling. The resulting energy demand intensity (kWh·m^{-2}·a^{-1}) is displayed for all 8 cases, 4 for the smallest ones and 4 for the largest ones.

The questions around XMY feasibility rest on whether (a) results for the largest energy demand across building type arose in the same meteorological year or (b) that all the nth largest demands that came from the same year across all building types is sufficiently close to their peaks as to represent a negligible difference for decision-making.

About (a), results indicate that minima and maxima per location are shared across building types in 26/36 of the locations for peak heating energy demand and 23/36 for cooling. Hence, and as expected, there is no single year for every location that leads to peak energy heating/cooling energy demand in the multi-year period because weather impacts different buildings differently.

About (b), finding the same year that caused the largest energy demand for heating/cooling per location across all building types showed significant variability. As indicated above, there is a single year for 26/36 locations that caused the peak demand for heating, and another for 23/36 for cooling. The case with the poorest fit for heating was that of Honolulu, where the n-largest year was the 16th year (1955). This meant that 1955 was the common year to all 4 building types that had the largest energy demand for heating. Here, heating energy demand peaked in 3 building types, but represented the 83rd quantile for the medium office. Similarly, for cooling, the poorest fit was Resolute Bay, with year 22nd (1968), corresponding to quantiles 71 to 95 across all four building types.

Based on the analysis, it was possible to estimate that XMYs are feasible to identify peak energy demands within ±5 kWh·m^{-2}·a^{-1} when said demands are greater than 20 kWh·m^{-2}·a^{-1}. The latter represent very low-energy buildings, and, at such levels of performance, tolerances cease to be informative, and buildings are rather insensitive to weather conditions.

Overall, this near-extreme approximation is judged acceptable for decision-making in building energy modelling, given its magnitude.

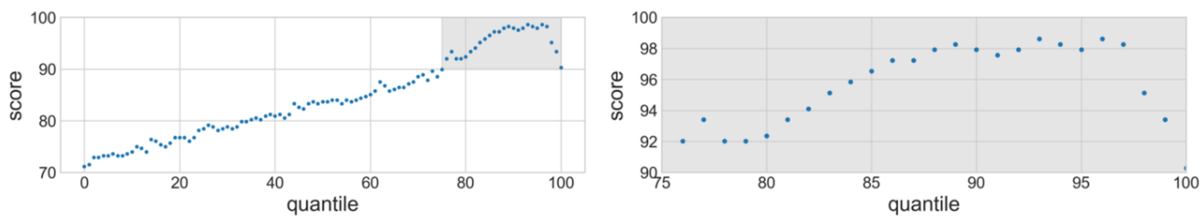

Figure 4: Performance of different quantiles in capturing near-extreme energy demands (left: global results across all quantiles with a step size of 1; right: zoomed view of the region with best performance marked with darker background)

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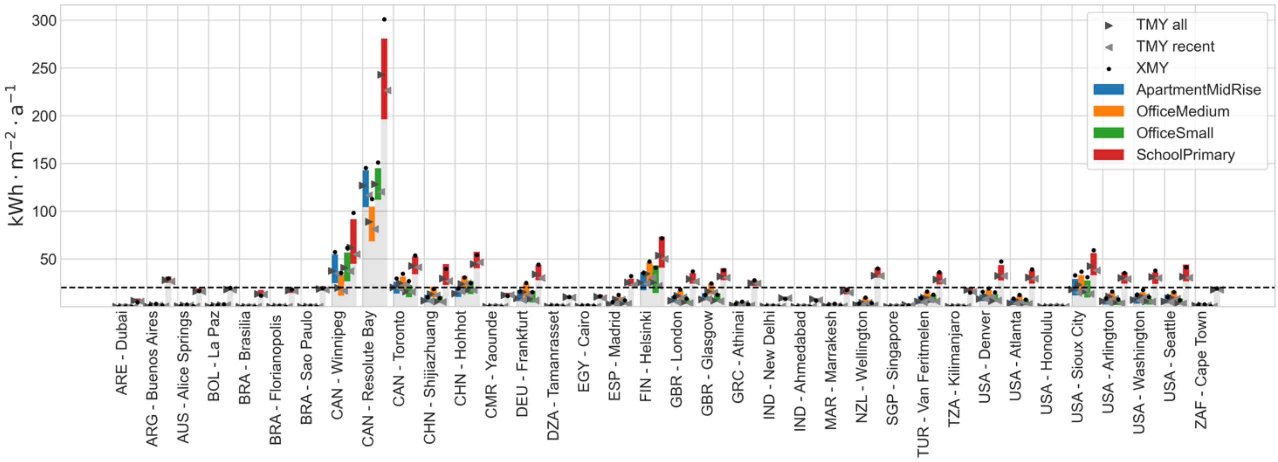
XMY performance

As presented in the methods section, a novel take for XMYs in this study is the consideration of a flexible heating/cooling season definition (Figure 1). This, based on the proportion of HDD and CDD per month over all years in the dataset, was introduced to cater for the diversity of climate zones featured across all continents, since there are locations clearly dominated by heating or cooling year-round (e.g., Resolute Bay and Dubai, respectively), and all options in-between (e.g., Buenos Aires, New Delhi, Cairo). In both HDD and CDD calculations, the chosen baseline temperature was 18 °C as an initial value to explore in this study. Since the resulting seasons are exclusively based on location and weather data, it was considered within the restrictions of using information that is agnostic to building stock characteristics.

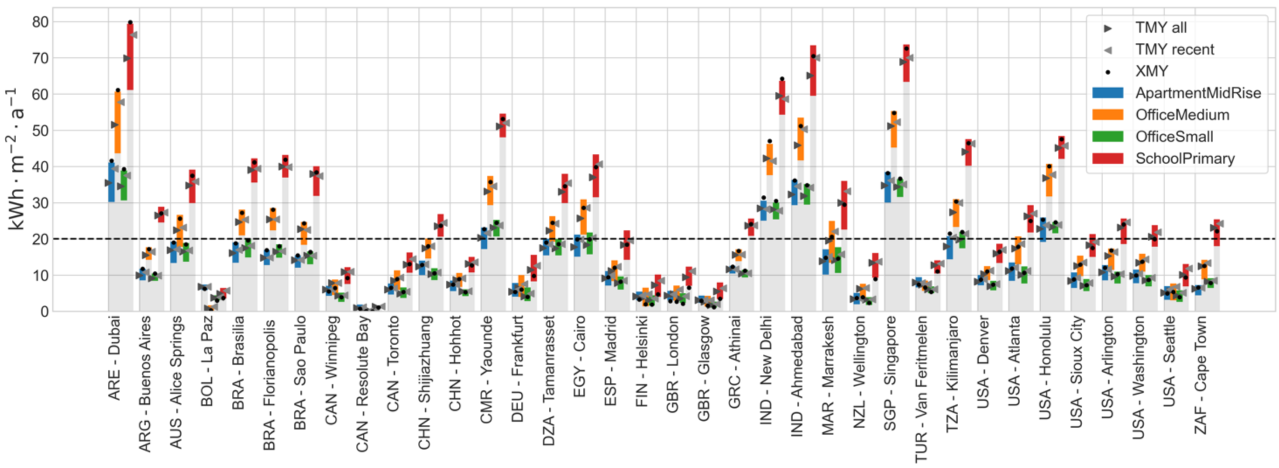
This novel recipe for XMYs based on quantiles was then implemented, using only HDD/CDD information, with HDD or CDD prioritized according to heating and cooling seasons. Given the exploratory nature of this work, all possible quantiles were scored based on the percentage of cases that meet the tolerances that make XMY-type definitions feasible (Figure 4).

The overall trend across quantiles showcases the reasoning in the methodology of an interval where performance peaks in between the extremes (Figure 4). Considering an XMY made up by months that displayed peak energy demands (maxima at quantile 100) shows a poor performance: this represents an extreme not observed in the multi-year dataset. Similarly, choosing the warmest months for heating and coolest for cooling also deteriorates performance (minima at quantile 0).

The optimal interval is located at about the 95th quantile, peaking for the 96th and 93rd (Figure 4). The reason for multiple solutions is that energy demands for heating and cooling are aggregated annually, not just within the relevant season. This is because buildings can display heating and cooling energy demands within the same month in some locations. Attempting definitions that meet energy demand, making exclusive use of the period within the relevant season, would fail for such locations, and it would lead to artificially extreme seasons for the rest. Since the interpretability of single-year composite weather files is considered an important feature for XMYs (particularly since the monthly composition is familiar to TMY users), such an approach is deemed not only appropriate but desirable.



(b) Heating



(b) Cooling

Figure 5: Overview of energy demand across all locations, building types, and XMY and TMYs performance

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Based on the previous results, the 96th quantile was selected as the optimal one. This represented an approximation to the true solution as the score is estimated using the lookup table built with the results of the multi-year simulations (all 8916 cases). Next, weather files were built using the EnergyPlus EPW file format based on the selected months with the quantile recipe. Simulations were then run with these weather files (144 cases, arising from 36 locations and 4 building types). Results for energy demands were extracted and compared to expectations based on the lookup tables. The approximation was here observed to be excellent, with an error under 0.5 $kWh \cdot m^{-2} \cdot a^{-1}$ for both heating and cooling demands.

Overall results show the performance of the XMYs selected for the 96th quantile in the context of the multi-year range obtained via simulation of meteorological years (MYs) (Figure 5). Results are also contextualized by the two sets of TMYs: those that consider all MYs in the weather database (the average of 62 years per location), denoted 'TMY all', and those that consider only the last 15 years, denoted 'TMY recent'.

As expected by the score of 98 (Figure 4), XMYs approximate well 282 cases of the 288 total (36 locations × 4 buildings × 2 modes, heating and cooling). This is considering valid tolerances of ±5 $kWh \cdot m^{-2} \cdot a^{-1}$ for cases with energy demands above 20 $kWh \cdot m^{-2} \cdot a^{-1}$. The 6/288 cases that do not satisfy the criteria are:

1. Winnipeg (climate class 7) – Primary School: absolute tolerance is +6 $kWh \cdot m^{-2} \cdot a^{-1}$ for a heating demand of 92 $kWh \cdot m^{-2} \cdot a^{-1}$ (6%).
2. Resolute Bay (climate class 8) – Medium Office: absolute tolerance is +8 $kWh \cdot m^{-2} \cdot a^{-1}$ for a heating demand of 105 $kWh \cdot m^{-2} \cdot a^{-1}$ (8%).
3. Resolute Bay (climate class 8) – Small Office: absolute tolerance is +6 $kWh \cdot m^{-2} \cdot a^{-1}$ for a heating demand of 145 $kWh \cdot m^{-2} \cdot a^{-1}$ (4%).
4. Resolute Bay (climate class 8) – Small Office: absolute tolerance is +20 $kWh \cdot m^{-2} \cdot a^{-1}$ for a heating demand of 281 $kWh \cdot m^{-2} \cdot a^{-1}$ (7%).
5. Shijiazhuang (climate class 4B) – Primary School: absolute tolerance is –6 $kWh \cdot m^{-2} \cdot a^{-1}$ for a heating demand of 45 $kWh \cdot m^{-2} \cdot a^{-1}$ (-11%).
6. Marrakesh (climate class 2B) – Primary School: absolute tolerance is –7 $kWh \cdot m^{-2} \cdot a^{-1}$ for a heating demand of 36 $kWh \cdot m^{-2} \cdot a^{-1}$ (–18%).

Global remarks

The sequencing of decisions to arrive at the formulation for XMYs may be argued to be influential to outcomes and needs further justification in the face of alternatives. For example, different or additional variables to HDDs and CDDs, time intervals other than months, or alternative heuristics. The approach developed here may be suboptimal compared to alternatives such as black-box or machine-learning ones. However, this is not an issue here since the approach first showed the allowable tolerances that must be accepted for XMYs to exist and that are independent from specific formulations. In addition, the quantile-based heuristic seems successful enough (282/288 cases), and performance appears even better than those of TMYs in the dataset, which are often not centered in the intervals ('TMY all').

Considering 'TMY all' against 'TMY recent' shows how the latter are getting distinctively warmer, as already noted by Crawley & Lawrie (2021). Similarly, meteorological records considered for XMY creation could focus only on recent years to capture the effects of a heating climate. The implications for the quantile-based formulation would then warrant further analysis. For this reason, we considered long-term records, with an average of 62 years per location. Thus, the smallest step for this approach is 1/62, or about 1.6. Focusing on the last 15 years would mean 1/15 or 6.6, so the second-highest option would be the 93rd quantile – a significant loss in resolution to find optimal fits.

Limitations and future work

Concerning XMYs, the following ideas are noted.

1. This study has established that it should be possible to achieve XMYs with a tolerance of ±5 $kWh \cdot m^{-2} \cdot a^{-1}$ for cases with demands above 20 $kWh \cdot m^{-2} \cdot a^{-1}$. However close, this work did not meet these criteria for all cases. Other XMY formulations would be worth exploring using the framework established here.
2. A fixed definition could be easier for end-users to get familiar with, as it would be similar across all locations in the world (save monthly composition). It would be worth evaluating how the flexible seasonal definition for heating and cooling compares to the fixed one of 6-month intervals in previous studies.
3. This work used a single baseline definition for HDD and CDD at 18 °C. It would be worth exploring the influence of this decision, and if having a deadband as wide as thermal comfort might allow for would lead to noticeable differences in performance.
4. The building characteristics for each building type here yielded low energy ones – those with demands for heating and cooling under 20 $kWh \cdot m^{-2} \cdot a^{-1}$. As shown, the multi-year variability in results is too small to be meaningful for resilience appraisals and thus considered outside the scope of interest for XMY work. Future work should include buildings with higher demands, as that is more representative of the existing, more vulnerable building stock worldwide.
5. Extend validation routines to locations not considered in the testing and development of XMYs.

For the quantile approach developed here:

1. This recipe peaked at a score of 98 when forcing all months in the selection to belong to the same quantile and for both heating and cooling. Relaxing these conditions might improve performance.
2. A multivariate formulation may be included to consider solar radiation or windspeed, as it has been argued necessary for other families of weather files like TMYs. Although selections are dominated by air temperature, further variables may help given issues at climate zones 7 and 8.

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Conclusions

This work advanced the definition of eXtreme Meteorological Years (XMYs), which captures the peak energy demands for building heating and cooling across years on record with a single-year composite weather file. Building on past research on them, it has:

1. Demonstrated that XMYs formulations are feasible despite different buildings not displaying peak energy demands on the same years, with a tolerance of ±5 kWh·m^{-2}·a^{-1} for cases with demands above 20 kWh·m^{-2}·a^{-1} being established as a result and expected, which is negligible in practical applications.
2. Established a framework that allows the rapid development, testing, and validation of different XMY recipes.
3. Found a simple formulation based on quantiles that works for 98% of cases considered here, and
4. Identified new opportunities for XMY development.

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