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A Comparative Analysis of Different Weather Datasets for Future Proofing Building Performance Analysis

Mitra Azimi[1,2], Juan-Carlos Baltazar[1]
[1]Texas A&M University, College Station, TX
[2]Gensler, Houston, TX

Abstract

The availability of diverse weather datasets in building energy modeling has raised questions regarding the selection of appropriate weather data considering growing concerns about climate change's impacts on the built environment. This study uniquely integrates Finkelstein-Schafer (FS) Statistics to evaluate the closeness of Typical Meteorological Year (TMY) files to the long-term climate average and future projections. In addition to the statistical analysis of weather files, the study employs fifty-two Actual Meteorological Year (AMY) files, four TMY files and twelve future climate projection files in building energy simulation of ASHRAE 90.1-2013 secondary school prototype building situated in a hot and humid climate. Results revealed that energy models utilizing TMY weather files tend to underestimate total energy consumption and heating loads, while simultaneously overestimating cooling loads. The findings underscore the necessity of adopting a multiyear energy modeling approach for informed design decision-making.

Introduction

The prevailing interpretation of building performance is a concept that enables the quantification of how effectively a building fulfills its intended function. It is commonly associated with aspects such as the energy efficiency of buildings, indoor environmental quality, thermal comfort, and lighting (de Wilde, 2019). Four primary approaches to building performance analysis include physical measurement, building performance simulation, expert judgment, and stakeholder surveys (Al-Shemmeri, 2011). Building performance simulations serve various purposes, including aiding in building design (e.g., Ashrafian, 2023), selecting cost-optimal technology measures (e.g., Moradi et al., 2023), predicting energy performance (e.g., Mahdy et al., 2022), determining comfort and indoor air quality conditions (e.g., Hosseini et al., 2022; Grassie et al., 2023), assessing building certification (e.g., Amiri et al., 2019; Scofield et al., 2021), and estimating potential energy savings for policy initiatives (e.g., Tsangrassoulis et al., 2017). Building performance analysis is integral to approaches like performance-based building design and contributes to high-performance buildings, showcasing ambitions beyond legal mandates (De Wilde, 2019). The common practice involves conducting building performance simulations with estimated input parameters, as the precise true values are often unknown (Sun et al., 2014). These estimations directly impact the accuracy and reliability of the simulation outcomes. Factors that contribute to uncertainties in building energy simulations include: 1) human factors, such as occupants' habits or schedules and physiological conditions, 2) building factors, including thermal characteristics of building materials, 3) climatic information 4) energy modeling tool's algorithms (Yu et al., 2022).

Addressing the question, 'Does It Matter Which Weather Data You Use in Energy Simulations?' (Crawley, 1998), the current literature lacks a consensus on the preferred weather file for building performance studies. Previous research commonly tackled this question by comparing building performance simulation results using different weather files or revising the methodology for generating a new Typical Meteorological Year (TMY) file. This study adopts a comprehensive approach, utilizing Finkelstein-Schafer (FS) statistics to analyze the closeness of TMY files to the long-term period for each weather variable, assessing whether a single weather file adequately represents the climatic conditions of a location for different performance analyses. While the application of FS statistics to generate TMY files is not uncommon, the uniqueness of this study lies in employing FS statistics to magnify the closeness of TMY files to the long-term climatic conditions.

Additionally, the emergence of new tools for statistical downscaling of Global Climate Models (GCMs) raises the question of which TMY should serve as the baseline climate. In an innovative approach, this study explores utilizing three TMYx weather files in addition to TMY3 file to generate more future projections, offering insights into the impact of the reference year on downscaling output. Weather files that were used for this study comprise three types: 1) fifty-two AMYs files, 2) four TMYs files, 3) and twelve future climate projection datasets for the George Bush International Airport weather station in Houston, TX.

Literature Review

A weather file is a collection of different weather or climatic parameters such as temperature, humidity, wind, and solar radiation. Ensuring good representation of three or four weather variables simultaneously is challenging, especially when historical series are short, and climate is subject to high variability (Pernigotto et al., 2017). Different statistical tests may be applied to weather data to determine which months or conditions should be included in the TMY. For example, statistical techniques, such as the Kolmogorov–Smirnov test as applied by Festa & Ratto (1993), and Finkelstein–Schafer tests as utilized by Hall et al. (1978) were employed for generating TMY files. The latter, which was used for generating TMY3 file, has gained popularity to construct a representative or average year, outlined in the reference (Wilcox & Marion, 2008). Alternative procedures suggested in the literature, such as the Festa-Ratto method and the Danish method, have not gained extensive attention in the scientific community and are infrequently employed (Costanzo et al.,2020). All these statistical methods for generating a typical year, however, can be executed for one weather variable at a time to identify months that deviate significantly from the long-term average trends for a specific variable, rather than aiming to create a well-balanced representation of all-weather variables simultaneously (Pernigotto et al., 2017).

Moreover, these approaches can be somewhat subjective, meaning they may rely on judgments or preferences rather than strict statistical criteria. The reason for overlooking statistical significance is often a deliberate choice. The goal is to create a synthetic year that closely mirrors certain aspects of the actual climate for specific use of typical year weather data, even if it means sacrificing some statistical rigor (Chan, 2016). For example, TMY files are created by assigning weights to various meteorological parameters based on their relative importance. However, there is no consensus on the selection of weather parameters or their corresponding weighting in the methods used to generate TMY files (Pernigotto et al.,2014). As an alternative, some other studies suggested customizing weighting factors for each system type (Chan, 2016).

The impact of utilizing a TMY weather file in building energy simulation outcome has been discussed in several studies previously. Some studies found that the application of typical meteorological files for building energy simulation results in over or under-estimated peak loads, building Energy Use Intensities (EUI), or overheating or thermal comfort depending on the building type or climate zone (e.g., Yang et al., 2014; Jentsch et al., 2014; Cui et al., 2017; Erba et al., 2017).

Moreover, the longevity of buildings, often exceeding 50 years, underscores the importance of evaluating their long-term performance (Hong et al., 2013). Prior research has highlighted substantial changes in weather conditions that cannot be overlooked (e.g., Cui et al., 2017; Siu et al., 2020). TMY files provide historical averages but lack the capability to depict extreme events, making them unsuitable for representing future climate conditions (Yassaghi et al., 2020). This limitation can result in system designs that fail to achieve the anticipated performance, as highlighted by Athienitis and O'Brien in 2015. In another study, Kneifel and O'Rear (2016) examined utilizing TMY3 weather file in calculating solar photovoltaic (PV) production for Net-Zero Energy (NZE) homes. Despite observing fluctuations in annual household electricity use, the researchers concluded that the TMY3 file may not be suitable for predicting typical annual household consumption and solar PV production due to the variability in weather conditions from year to year.

Recent development of TMYx weather files, which are based on hourly weather data up to 2021, have rekindled interest in using typical-year files for building performance simulations. Several studies have highlighted significant differences in energy consumption outcomes when comparing the older TMY files with the newer TMYx files. These investigations consistently observed higher dry-bulb temperatures in the TMYx files as compared to the older TMY files (e.g., Evola et al., 2021; Mahdy et al., 2022; Brown et al., 2023).

Improvements in computational capabilities enable utilization of multiyear simulations using Actual Meteorological Years (AMYs). The AMY weather dataset contains detailed hourly meteorological and solar radiation data for a particular location over the entire year. Typically, AMY weather files are generated based on observed data collected from a nearby airport weather station (Azimi & Baltazar, 2022). Various studies, including those conducted by Huang et al. (2018), Sun et al. (2015), and Zhang et al. (2016), recognized the improved performance of design methods utilizing multi-year weather data. Sun et al. (2014) observed reduced risks of improper system sizing in AC system design for Atlanta's subtropical humid climate when employing multi-year weather data.

Despite the AMYs' benefits mentioned above, TMY-based Building Performance Simulations (BPS) is still prevalent due to the convenience of accessing TMY weather files from freely available databases (Moradi et al., 2023). However, Classical approaches to estimating energy consumption with a single weather file may not be reliable due to climate change (Yassaghi et al., 2020). Climate change impact assessments typically rely on data generated by Global Climate Models (GCM) (Nik & Arfvidsson, 2017). Given that many building-related research projects use building simulation tools requiring annual hourly weather dataset, there is considerable emphasis on converting general climate change predictions into detailed hourly datasets. Belcher et al. (2005) outlined two main methodologies for constructing weather files for future climate scenarios in building thermal simulation: 1) analogue scenarios, and 2) downscaling GCMs. The Analogue Scenarios method entails utilizing present-day weather data from a location with a climate similar to the projected climate of the study site yet identifying suitable analogues for building simulation is challenging. Downscaling GCMs involves obtaining global climate projections from international inventories like CMIP5 and CMIP6, typically available at monthly and coarse spatial resolutions (Cox et al., 2015). However, assessing climate change's impact on building performance requires higher temporal resolution local weather data (Eames et al., 2012). Downscaling methods, ranging from simple techniques like statistical interpolation and morphing to more complex approaches such as stochastic weather generation and dynamic downscaling of GCMs, address this need (Guan, 2009).

The morphing method combines observed weather data with climate change projections through shifts and stretches in present-day weather time series, creating future climate representations (Dias et al., 2020). This methodology effectively reflects average weather condition changes, offering advantages such as a reliable baseline climate, meteorological consistency, simplicity, and spatial downscaling (Belcher et al., 2005). While widely used in building energy simulation (e.g., Crawley, 2008; Chan, 2011), the morphing method has faced criticism. Guan (2009) points out the lack of cross-correlation among different weather parameters. Some researchers note that morphed design weather data may not fully capture the character and variability of future climate, which could be different from the present-day climate. Consequently, monthly projections from GCMs may not account for potential extreme anomalies (Rodrigues et al., 2023). Addressing limitations in the original morphing approach, a later study introduced modified morphing algorithms to retain underlying climate projections, proposed by Arup and Argos Analytics. These algorithms were then utilized in developing the WeatherShift™ tool (for details of revised methodology, see Dickinson & Brannon, 2016; Eames et al., 2023).

Several studies have proposed the utilization of stochastic weather generators, employing probabilistic methods, for generating future climate data for building simulation. Weather generators, in theory, can produce enough data to assess the likelihood of extreme weather events (Ababaei et al., 2010). They employ algorithms to generate extended time-series data for weather variables, replicating statistical properties akin to historical records. Weather generators encounter a notable constraint as they depend on statistical data from past weather observations. This limitation can lead to inaccuracies, particularly in depicting rare extreme events that might not be present in the limited historical data used to create the generator (Tootkaboni et al., 2021)

Dynamical downscaling employs a nesting strategy to acquire climate information at a resolution of 2.5–100 km², utilizing a Regional Climate Model (RCM) to derive local or regional climate details. This method simulates atmospheric and land surface processes while considering topographical data, land–sea contrasts, and other Earth-system components. The RCM-generated climate information features finer spatial resolution compared to GCMs (Nik & Arfvidsson, 2017), enabling better representation of local climate variability, and ensuring physically consistent datasets. Despite requiring substantial computational power and storage, the accuracy of the underlying GCM influences the output quality. To address uncertainties, different GCM–RCM pairings are combined (Tajpour et al., 2020). At present, dynamically downscaled future weather files in readily usable .EPW formats are relatively scarce compared to morphed data. Nevertheless, there have been instances where certain countries, like Belgium and Canada, have already made downscaled files accessible (Brown et al., 2023).

Methodology

The methodology section of this study is organized into two primary segments. The first segment is dedicated to the analysis of variations within weather files. This involves a detailed examination of the data to identify and quantify the differences and changes in the weather parameters over the study period. The second segment focuses on assessing the influence of these varying weather files on the performance of a standard building model. This includes the evaluation of energy consumption, cooling, and heating loads as performance metrics under different weather conditions. The combined analysis aims to understand how discrepancies in weather data can affect building performance, thereby aiding in the development of more resilient and efficient building designs.

Data Collection and Data Process

Actual Meteorological Year (AMY). Actual Meteorological Year (AMY) weather datasets from 1970 to 2021 for the George Bush International Airport weather station in Houston, TX (belonging to hot and humid climate, were obtained from NOAA Local Climatological Data, using the NCEI Climate Data Online Map Server (NCEI, 2023). Actual meteorological data obtained from LCD does not include solar radiation data. The actual meteorological year data in 1970, 1971, and 1972 contain measured data every three hours. Also, some of the actual meteorological year files had missing data. In this case, a linear interpolation was used between two values to fill the gap. The trend was adjusted linearly to ensure continuity with the data immediately after and before the gap. In cases with gaps larger than six consecutive hours were not filled, and the hourly observations were labeled as "missing" data (Baltazar and Claridge, 2006). Moreover, because the data values from the LCD dataset are given in I.P. units, the AMY dataset units were converted to S.I. units, so all data become consistent in units to convert to EPW format later. The next step was converting the CSV format to EPW files because CSV format data is not readable by building energy simulation tools. The EnergyPlus Weather Statistics & Conversions app converted .CSV format data to EPW format data, where corresponding EPW missing codes replaced missing values (Big Ladder Software, n.d.). The methodology to process AMY datasets is shown in Figure 1.

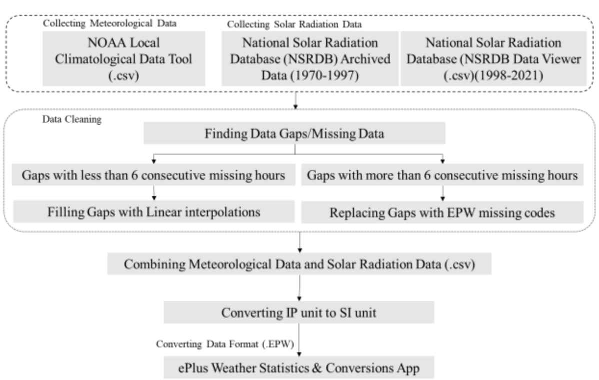

Figure 1 Methodology for AMY Weather File Dataset Collection

Typical Meteorological Year (TMY). The TMY file creation involves selecting a typical meteorological month (TMM) for each of the 12 calendar months through statistical analysis and concatenating these 12 selected months to form a typical meteorological year (TMY) weather file. The process involves statistical analysis and concatenating these 12 selected months (TMMs) to form a TMY weather file. The selection judges the 'closeness' of each year to the composite of all years, assessed through the cumulative distribution function (CDF). The final month choice also considers the persistence of weather patterns. This study obtained a TMY3 weather file and three typical year weather files for specific “x” periods (TMYx) from the online repository Climate.OneBuilding.org. TMYx files include periods for 1970-2021, 2004-2018, and 2007-2021. All TMY3 and TMYx files are derived from hourly weather data in the US NOAA's Integrated Surface Database (ISD). (Table 1).

- Table 1 Typical Meteorological Year Data Collection

Weather file	Reference Data Period
TMY3	1976 to 2005 (thirty years)
TMYx(1970-2021)	1970 to 2021(fifty-two years)
TMYx(2004-2021)	2004 to 2018 (fifteen years)
TMYx(2007-2021)	2007 to 2021(fifteen years)

Future Climate Projection Data. In this study, WeatherShift™ software was used to generate future climate projections. WeatherShift™ applies the morphing method to data from 14 out of approximately 40 available Global Climate Models (GCMs) from the Coupled Model Intercomparison Project Phase 5 (CMIP5). This tool provides future weather projection data for three time periods: 2026-2045 ('2035s'), 2056-2075 ('2065s'), and 2081-2100 ('2090s') in relation to a baseline period, considering two emission scenarios, RCP4.5 and RCP8.5. A 50 percentile (median) was chosen for the probability level. It's important to clarify that the percentile distribution of WeatherShift™ indicates likelihood, not projection confidence (Troup & Fannon, 2016). Traditionally, professionals rely on the TMY3 weather file as the reference period for generating future projections. In contrast, this study goes beyond convention by analyzing all four existing typical weather files to generate future projections. The aim is to scrutinize whether the choice of the reference year weather file significantly influences the morphing outcome.

The morphing methodology imposes the monthly future climate information extracted from GCMs on the present-day hourly weather data using three operations: (1) shifting, (2) linear stretching (scaling factor), and (3) a combination of shifting and stretching (Belcher et al., 2005), see Table 2.

Table 2 Three Different Morphing Algorithms to Generate Future Weather Data; adapted from Azimi et al. (2022)

Parameters	Algorithms
Atmospheric pressure & Relative Humidity	Shift: $x = x_0 + \Delta x_m$
Wind speed & Dew-Point Temperature[1]	Stretch: $x = \alpha_m \times x_0$
Dry-bulb temperature	$x = \Delta x_0 + \alpha_m \times (x_0 - \langle x_o \rangle_m)$

Where x is the future climate variable, Δx_m is the absolute monthly change derived from a GCM or a regional climate model (RCM), α_m is the fractional monthly change derived from a GCM or RCM and $\langle x_o \rangle_m$ is the monthly mean related to the variable x_o.

Finkelstein-Schafer (FS) statistics. The study employs Finkelstein-Schafer (FS) statistics to evaluate closeness of weather files in comparison to long-term average conditions spanning from 1970 to 2021. The methodology was initially introduced by Hall et al. (1978) for generating TMY files. The goal is to assess how effectively these weather files depict the long-term climate. Next the steps for their estimation are presented.

Step 1: Daily indices are calculated for each weather file in the record. Daily indices include maximum dry bulb temperature, minimum dry bulb temperature, mean dry bulb temperature, maximum dew point temperature, minimum dew point temperature, maximum wind speed, mean wind speed, total global radiation, and total direct radiation.

Step 2: Cumulative distribution functions (CDFs) for the daily indices are calculated for each month of each year in the record (fifty-two years). CDF is a statistical concept representing the percentage of values that are less than or equal to a specific index value.

Step 3: For each month of the calendar year, the long-term CDF is calculated.

Step 4: The monthly CDF of individual years is compared to the long-term CDF using each index's Finkelstein- Schafer (*FS*) statistics. *FS* statistics then quantify the weighted absolute difference between the short-term CDF (e.g., January of TMY3) and the long-term CDF (e.g., a composite of all fifty-two Januarys from 1970 to 2021), indicating how closely they match.

$$FS = \frac{1}{n} (\sum_{i=1}^{n} \delta_i$$

Where δ_i is the absolute difference between the long-term CDF and the month/year CDF at $x_{(i)}$ (i=1, …, n) and n is the number of daily readings in the month

Step5: For each weather variable, the FS statistics results are ranked in ascending order; smaller ranks indicates greater similarity to the long-term distribution. This ranking helps assess how well the methodology selects the typical meteorological month (TMM) for specific variables and months in each TMY file.

Building Energy Simulation

Building Description and Modeling Assumptions. The ASHRAE 90.1-2013 secondary-school prototype model was chosen for energy modeling to investigate the impact of weather input choices on the performance of building design alternatives. Building envelopes include the roofs, foundations, exterior walls, and windows. The reference building has no window shading element. shows the 3D view of the DOE secondary school prototype building model, and Figure 3 shows the space type breakdown of the model. The model has a flat roof with insulation above the roof deck (IEAD). The roof type uses the "non-residential" space type values and thermal conductance values for climate zone two. The model includes 4-inch (10-cm) heavyweight concrete slabs-on-grade with a layer of carpet and the exterior wall system is non-residential steel framed with thermal conductance values according also to climate zone two. The secondary school prototype building has fixed vertical exterior windows and skylights appear over the gymnasium zones (4.5% of the roof area). The minimum insulation characteristics of the secondary school prototype model based on ASHRAE 90.1-2013 for climate zone two are listed in Table 3.

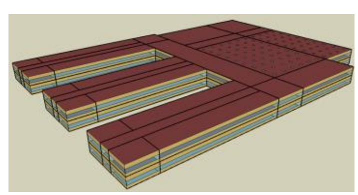

Figure 2 3D View of the DOE Secondary School Prototype Building Model

[1] Belcher et al. did not provide a method for morphing the base year relative humidity into future relative humidity. The algorithm comes from technical manual of CCWorldWeatherGen.

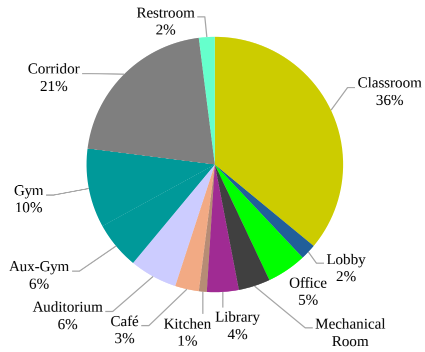

Figure 3 Space Type Breakdown of Secondary School Prototype Model

The HVAC system for the secondary school prototype model is based on the study of the 2003 CBECS dataset to reflect the systems installed in real buildings. The cooling system for the auditorium, gym, auxiliary gym, cafeteria, and kitchen is a two-speed Direct Expansion (DX) air conditioning unit with an efficiency of 9.8 EER and a COP of 3.399. Cooling in all other spaces is provided by an air-cooled chiller with a COP of 2.960. The package air conditioning units provide heating for the auditorium, gymnasium, auxiliary gymnasium, cafeteria, and kitchen using gas furnaces with an efficiency of 80% for these spaces. A gas-fired boiler provides heating in all other spaces with 80% thermal efficiency. Constant air volume (CAV) single area systems distribute air in the auditorium, gymnasium, auxiliary gymnasium, cafeteria, and kitchen. For other spaces, variable air volume (VAV) is used for ventilation and air-conditioning.

Table 3 Thermal Characteristic of Envelopes for Climate Zone Two

Envelope Type	Insulation
Roof	Insulation entirely above deck: Assembly Max= U-0.039 Insulation Min= R-25 c.i.
Wall Above the	Steel-framed: Assembly Max= U-0.084 Insulation Min= R-13
Slab on grade	Unheated: Assembly Max= F[3]-0.730 Insulation Min= NR
Floors	Steel Joist: Assembly Max= U-0.038 Insulation Min= R-30
Fenestration max U-factor (BTU/h·ft²·°F) Fenestration max SHGC	0% to 40% WWR Nonmetal framing all=U-0.40 For all frame types: 0.25
Skylights (0% to 3% of roof for CZ2)	Assembly Max= U-0.65 Assembly Max SHGC=0.35 Assembly Min. VT/SHGC= NR

U-factor (IP) BTU/h·ft²·°F
R-value (IP) ft²·°F/BTU
F-Factor (IP) BTU/h·ft²·°F

Discussion and Results

Statistical Description of AMY. Table 4 shows the statistics of hourly weather variables from 1970 to 2021. The results show that the maximum dry-bulb temperature was +43°C (109°F), recorded in 2000, and the minimum temperature was -14°C (7°F), recorded in 1989. The average long-term hourly dry-bulb temperature from 1970 to 2021 was 20°C (69°F). The average dry-bulb temperature of individual years varied from 18°C (65°F) in 1976 to 22°C (72°F) in 2017. As shown in Figure 4, the average dry-bulb temperature in the TMY3 weather file stood in the lower range, while that of TMYx (2004-2018) and TMYx (2007-2021) showed higher values.

Table 4 Statistics of Weather Variables from 1970 to 2021

	DBT(°C)	DPT (°C)	WS (m/s)	GHI (Wh/m^2)	DNI (Wh/m2)
AVG	21	15	3	193	184
MAX	43	30	25	1312	1415
MIN	-14	-22	-	-	-

The range of dry-bulb temperature was also calculated to quantitatively understand the variation inherent in the local climate. The result showed significant variation in hourly dry-bulb temperature range in individual years, with a minimum range equal to +38°C (100°F) in 2005 and a maximum range of +51°C (123°F) in 1989.

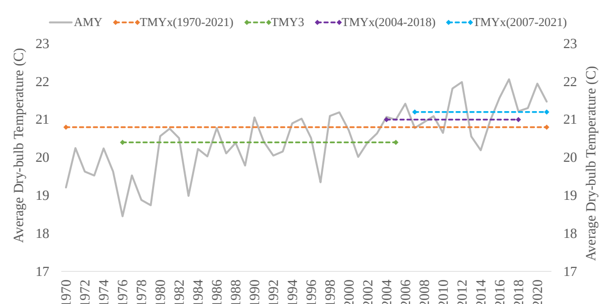

Figure 4 Average Dry-bulb Temperature

Hourly dry-bulb temperature from 1970 to 2021 showed a right-skewed distribution with a long tail on the left side see below Figure 5.

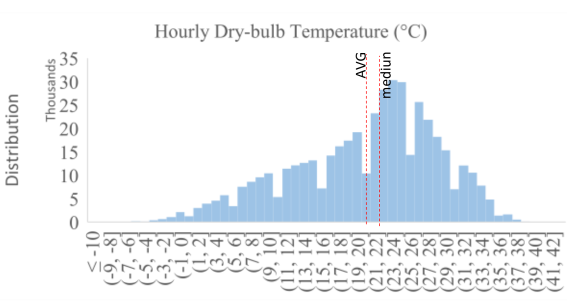

Figure 5 Hourly Dry-bulb Temperature Histogram

Statistical Analysis of TMY. This study also examined four typical year weather files generated using different lengths of reference data, using the same methodology for Houston, TX. The longest period of reference datasets in this study contains hourly measured weather data from 1970 to 2021. Table 5 shows the summary of dry-bulb temperature statistics in different reference datasets. Results show that the 15-year datasets have smaller ranges than those of 30-year and 52-year reference datasets. Results of statistical analysis of TMY weather files showed shorter ranges of dry-bulb temperature (Table 6) compared to their corresponding reference dataset. For example, TMYx (2004-2018) has the minimum dry-bulb temperature of -11°C (13°F), and the maximum temperature of +42°C (108°F). However, the dry-bulb temperature in TMYx (2007-2021) has a shorter range with a minimum of -1°C (31°F) and a maximum of +37°C (99°F). It can be concluded that typical year weather files do not capture the variation in the long-term climatic conditions due to the methodology to generate TMY weather files to exclude extreme events.

Table 5 Statistic of Dry-bulb Temperature (°C) in Periods of Reference Data

DBT	1970-2021	1976-2005	2004-2018	2007-2021
Min	-14	-14	-7	-11
Max	43	43	42	42
STD	8	8	8	8
Mean	20	20	21	21
Median	22	22	23	23
0.4%	-2	-2	0	-1
99.6%	36	36	37	37

Table 6 Statistic of Dry-bulb Temperature (°C) in TMY Weather Files

DBT	TMYx (1970-2021)	TMY3	TMYx (2004-2018)	TMYx (2007-2021)
Min	0	-6	-6	-1
Max	39	39	40	37
STD	8	8	8	8
Mean	21	20	21	21
Median	22	22	23	22
0.4%	2	-1	-3	2
99.6%	36	36	37	36

Statistical Analysis of Future Climate Projection. TMY3 and TMYx files were employed to generate future climate projections under the RCP8.5 scenario using the WeatherShift™ tool (morphing downscaling). As depicted in Figure 6 to Figure 9, all weather variables, except for wind indices, exhibited an increase compared to their corresponding reference data (refer to Table 7 for TMY3). It was also determined that the tool is incapable of morphing wind parameters under RCP8.5; consequently, the future projections are not deemed reliable for wind analysis. It should be noted that WeatherShift™ has been updated based on IPCC AR6 scenarios recently, although this update was not investigated in the current study.

Table 7 Statistic of Mean Dry-bulb Temperature (°C) in Future Weather Projections under RCP8.5

Reference Weather File	RCP 8.5(50%) 2026-2045	RCP 8.5(50%) 2056-2075	RCP 8.5(50%) 2080-2100
TMY3	23 (+11%)	23 (+15.2%)	25 (+20.6%)
TMYx(1970-2021)	22 (+7.5%)	24 (+14.9%)	25 (+20.1%)
TMYx(2004-2018)	23 (+7.4%)	24 (+14.7%)	25 (+19.9%)
TMYx(2007-2021)	23 (+7.3%)	24 (+14.6%)	25 (+19.8%)

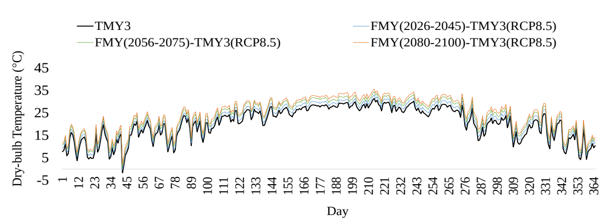

Figure 6 Time-series plot of Average DBT of TMY3 and Future Projections Generated Using Weather Shift under RCP8.5 Scenario

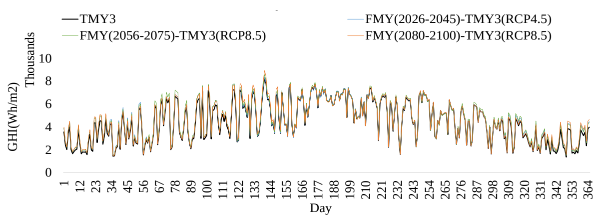

Figure 7 Time-series plot of Daily GHI of TMY3 and Future Projections Generated Using Weather Shift under RCP8.5 Scenario

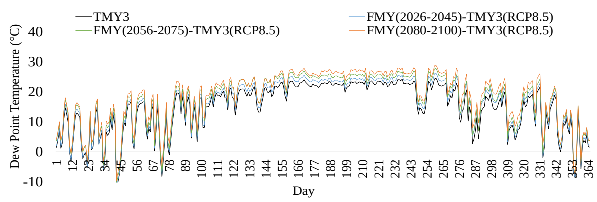

Figure 8 Time-series plot of Daily Average DPT of TMY3 and Future Projections Generated Using Weather Shift under RCP8.5 Scenario

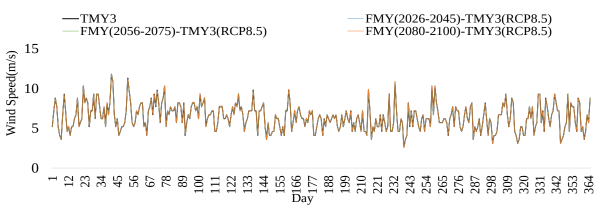

Figure 9 Time-series plot of Daily Maximum Wind Speed TMY3 and Future Projections Generated Using Weather Shift under RCP8.5 Scenario

Analysis of Typical Meteorological Month (TMM). Comparing typical year weather files reveals significant differences in the arrangement of typical months, despite all TMY weather files being generated using the ISO 15927-4:2005 methodology. Table 8 provides a summary of the results. Interestingly, even though both TMYx(2004-2018) and TMYx(2007-2021) were created using the same methodology, fifteen years of reference measured data from the ISD[2], the selection of Typical Meteorological Months (TMMs) differs for each calendar month. When comparing TMY3 and TMYx(1970-2021), only five TMMs (June, July, August, September, and November) are common. Notably, TMYx(2004-2018) and TMYx(2007-2021), which share a subset of the reference data used for TMYx(1970-2021), have no common TMMs. Lastly, TMYx (1970-2021) lacks TMMs selected from 2005 to 2021.

It was concluded that the choice of reference data and the length of the reference period significantly impact the selection of Typical Meteorological Months (TMMs). Therefore, when using these weather files for building performance simulations, it is crucial to consider the implications of the specific TMY file chosen, as it can influence the results and design decisions.

Table 8 Comparison of Typical Meteorological Month (TMM) of four TMY weather files

Weather File	TMY3	TMYx(1970-2021)	TMYx(2004-2018)	TMYx(2007-2021)
Reference Years	1976-2005	1970-2021	2004-2018	2007-2018
Number of Years	30	52	15	15
January	1987	1995	2008	2019
February	1981	1992	2011	2013
March	1988	1999	2011	2016
April	1990	2004	2010	2014
May	1986	2004	2008	2017
June	2000	2000	2012	2015
July	1991	1991	2014	2017
August	1998	1998	2007	2012
September	1988	1988	2010	2015
October	1977	1992	2007	2017
November	1990	1990	2008	2010
December	1980	2002	2011	2018

Results of Finkelstein-Schafer (*FS*) Statistics. Monthly Cumulative Distribution Function (CDF) curves of ten daily indices of AMY and TMY weather files were compared to the composite of fifty-two years (from 1970 to 2021) for the corresponding month. Daily indices include maximum, minimum, and mean dry bulb temperature, dew point temperature, maximum and mean wind speed, and total Global Horizontal Irradiance and Direct Normal Irradiance. These indices were examined by the ranking of F.S. statistics of all typical year weather files in this study to find out how well a Typical Meteorological Month (TMM) was chosen to represent the averageness of long-term conditions for each index.

As shown in Figure 10, Typical Meteorological Year (TMY) weather files, while generally representing long-term conditions closely, do not account for extreme cold or hot events due to the methodology used in their generation. Figure 11 illustrates the shift towards higher daily average dry-bulb temperatures in July when compared to both the long-term average spanning from 1970 to 2021 and the reference file used for downscaling (in this case, TMY3). This indicates that TMY files may not accurately represent potential climate variations in the future, which is crucial for building design and energy performance assessments.

[2] US NOAA's Integrated Surface Database

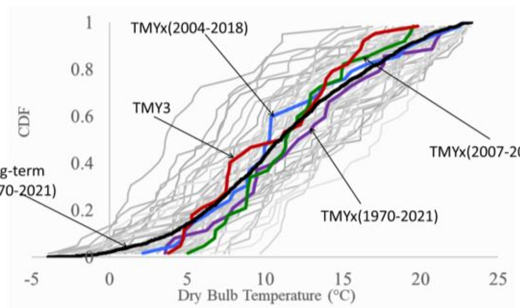

Figure 10 CDF of Daily Average DBT in January of Fifty-two AMY Files vs. TMY Files

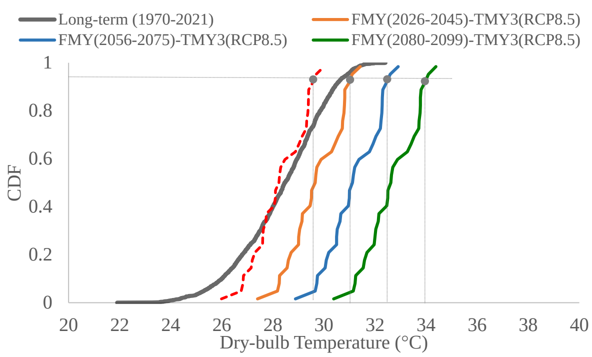

Figure 11 CDF of Daily Average DBT in July of FMY files Under RCP8.5 vs. their Corresponding Reference Year (TMY 3)

Notably, the *FS* statistics of AMY weather files revealed significant differences in the summer months (June, July, and August) for all indices. To put it simply, this means that the cumulative distribution functions (CDFs) for these months in individual years differed significantly from the CDF of the composite of fifty-two years for the same months (see Figure 12). This suggests that the choice of a typical month for the summer season has a degree of uncertainty compared to other months. In other words, the weather conditions during the summer months vary significantly from year to year, and the chosen month may not be reliable to represent a typical climatic condition.

To better understand the closeness of different weather files to the long-term average, the *FS* statistic results of four TMY files were ranked alongside those of AMY files for all weather indices, as shown in Table 9 to Table 12. In these tables, smaller ranks indicate closer alignment with the long-term average. Therefore, in each table, ranks smaller or equal to five were highlighted in

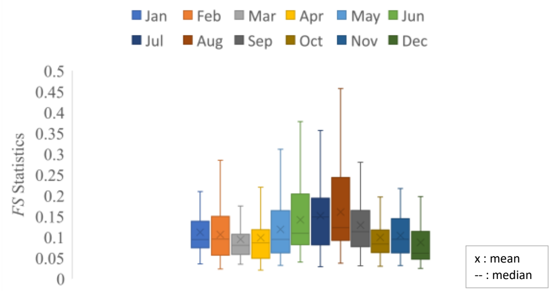

Figure 12 FS Statistics of Monthly Maximum Dry-bulb Temperature

gray. It's important to note that the FS statistical test cannot analyze all weather indices simultaneously. Notably, TMY3 demonstrated better consistency for temperature indices with the long-term average spanning from 1970 to 2021 compared to other typical year weather files. Although TMYx(1970-2021) was compared to its corresponding reference period, it showed higher ranks for all indices. These results underscore the impact of assigning weighing factors to weather indices in the methodology for generating TMY files. Furthermore, the FS statistics revealed that none of the TMY weather files closely matched the long-term average for solar radiation and wind indices.

Table 9 Ranking of F.S. Statistics of TMY3 File

Index\Rank	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	AVG-RANK
Max-DBT	25	6	13	7	21	15	11	20	43	3	30	26	18
Min-DBT	9	13	17	8	2	10	17	29	6	38	7	7	14
AVG-DBT	13	6	16	2	10	13	13	3	23	34	15	2	13
Max-DPT	17	22	9	22	19	25	26	25	9	44	10	28	21
Min-DPT	5	18	22	4	24	9	5	20	17	38	13	2	15
AVG-DPT	9	10	20	19	17	12	15	19	10	39	13	12	16
MAX-WS	5	10	31	25	21	18	24	51	39	17	5	7	21
AVG-WS	22	17	46	31	11	21	14	51	47	11	22	22	26
Total-GHI	10	15	6	30	25	42	19	21	5	9	7	19	17
Total-DNI	6	4	6	28	16	45	25	28	4	3	8	2	15
AVG-RANK	12	12	19	18	17	21	17	27	20	24	13	13	18

Table 10 Ranking of FS Statistic of TMYx(1970-2021) File

Index\Rank	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	AVG-RANK
Max-DBT	5	15	11	55	37	36	13	21	54	54	32	11	29
Min-DBT	7	19	11	43	38	42	13	24	38	54	6	20	26
AVG-DBT	10	21	14	47	33	32	15	6	44	54	14	8	25
Max-DPT	15	12	23	51	37	42	27	36	43	52	9	9	30
Min-DPT	20	28	27	51	45	52	7	21	47	54	14	20	32
AVG-DPT	16	17	30	50	39	40	14	20	46	54	11	21	30
MAX-WS	50	21	26	56	55	54	25	52	55	54	4	26	40
AVG-WS	53	9	33	54	52	48	9	52	52	56	21	35	40
Total-GHI	4	9	26	56	55	50	21	22	54	53	25	48	35
Total-DNI	11	36	36	56	55	53	48	39	55	54	26	47	43
AVG-RANK	19	19	24	52	45	45	19	29	49	54	16	25	33

Table 11 Ranking of F.S. Statistics of TMYx(2004-2018) File

Index\Rank	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	AVG-RANK
Max-DBT	2	35	45	31	49	47	7	5	13	37	56	23	29
Min-DBT	19	46	41	28	53	50	9	41	46	23	54	25	36
AVG-DBT	3	40	38	22	49	49	7	10	35	39	55	21	31
Max-DPT	2	40	26	27	47	41	9	35	48	7	56	25	30
Min-DPT	23	38	13	23	51	53	17	42	41	4	55	9	31
AVG-DPT	6	40	19	24	51	47	19	41	44	3	56	18	31
MAX-WS	55	40	29	43	53	56	49	29	50	19	56	35	43
AVG-WS	44	32	12	22	53	51	47	19	16	15	56	16	32
Total-GHI	15	46	43	17	56	56	25	24	24	40	56	9	34
Total-DNI	17	48	42	19	56	56	22	12	26	42	55	16	34
AVG-RANK	19	41	31	26	52	51	21	26	34	23	56	20	33

Table 12 Ranking of FS Statistic of TMYx(2007-2021) File

Index\Rank	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	AVG-RANK
Max-DBT	16	38	54	2	14	8	20	37	18	18	10	28	22
Min-DBT	18	41	55	15	11	32	41	45	17	28	9	43	30
AVG-DBT	18	37	53	5	2	25	33	40	21	25	12	33	25
Max-DPT	30	26	55	8	15	15	24	44	14	35	3	18	24
Min-DPT	32	7	55	14	23	25	40	49	2	19	2	43	26
AVG-DPT	25	8	55	12	19	15	33	50	6	23	3	36	24
MAX-WS	26	49	56	30	51	44	52	54	48	27	49	30	43
AVG-WS	31	20	56	25	43	46	23	48	51	24	17	9	33
Total-GHI	40	49	56	45	43	31	55	53	39	46	48	40	45
Total-DNI	38	39	56	42	41	30	54	53	39	38	46	35	43
AVG-RANK	27	31	55	20	26	27	38	47	26	28	20	32	31

Results of Energy Simulations. The ASHRAE 90.1-2013 Secondary School Prototype Model was used to conduct energy simulations with different typical year weather files. The energy usage results using the TMY3 weather file showed that 58% of annual site energy consumption was electricity and 42% was natural gas. In detail, 46% of annual electricity was consumed for cooling, 29% for plug and process loads, 17% for fans, and 8% for lamps. Moreover, heating, kitchen gas equipment, and domestic hot water consumed 43%, 30%, and 27% of natural gas, respectively. As shown in Figure 13 and , there is an obvious difference in the responses of monthly building cooling loads and heating loads to climate variability.

The energy usage intensity (EUI) in simulations using all TMY files varied from 78.3 kBtu/sqft-yr in the energy model using TMYx(2007-2021) file to 80.3 kBtu/sqft-yr in the energy model using TMYx(2004-2018) file. The energy model by TMY3 showed the smallest cooling use and the largest heating consumption compared to other models. In contrast, the energy model using TMYx(2004-2018) showed the largest cooling consumption, and the energy model by TMYx(2007-2021) showed the smallest heating use.

The Energy Use Intensity (EUI) results from 1970 to 2021 varied between 76.7 kBtu/sqft-year in 2012 and 86.56 kBtu/sqft-year in 1978. On average, the EUI during this period was 80.5 kBtu/sqft-year. Comparatively, when using different typical year weather files (TMY3, TMYx (1970 to 2021), TMYx (2004-2018), and TMYx(2007-2021)), the EUI values

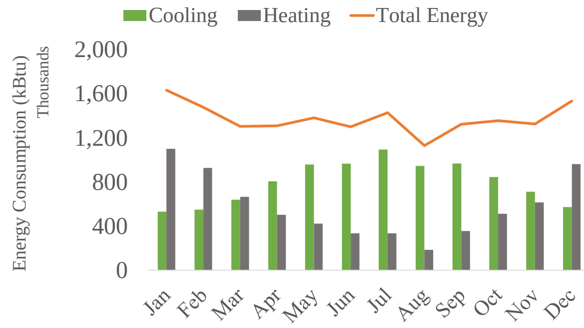

Figure 13 Monthly Cooling and Heating Usage of ASHRAE 90.1-2013 Secondary-School Prototype Model Throughout One Typical Year (TMY3)

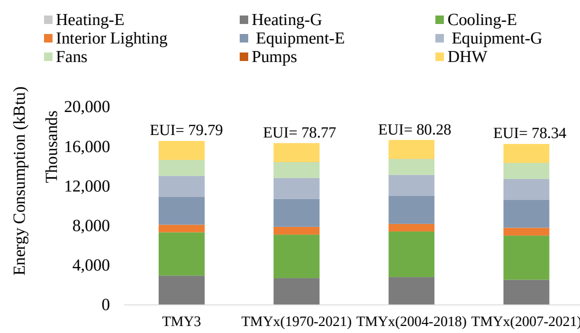

Figure 14 Total Annual Energy Consumption Results of ASHRAE 90.1-2013 Secondary School Prototype Model using TMY Weather Files

were 0.9%, 2.2%, 0.2%, and 2.4% lower than the average EUI from 1970 to 2021, respectively. These findings indicate that energy models using typical year weather files tend to underestimate energy consumption when compared to individual yearly data.

Furthermore, the total energy consumption using future climate projection datasets (under RCP8.5) exhibited an increase ranging from +0.8% to 1.5% in the early-century period (2026-2045) and from 5.3% to 6.4% in the late-century period (2080-2099) when compared to energy consumption based on their corresponding TMY weather files. Notably, energy models utilizing the future weather projection generated by TMYx(2007-2021) showed the largest increase among all other models for all three future periods. The EUI ranges from energy models using future climate projection datasets fell within the range of EUI results obtained from 52-years of AMY dataset covering the years 1970 to 2021. This observation suggests that energy models using historical weather files from 1970 to 2021 can provide reasonably reliable predictions of future energy consumption, see Table 13 below.

Table 13 Comparison of Energy Models using AMY and FMY files with that of TMY files

	Difference with AMY (1970 to 2021)	**Diff. with Corresponding FMY (RCP 8.5)**
TMY3	-3.9% to +8.5%	+0.8% to 5.3%
TMYx(1970-2021)	-2.7% to +9.9%	+1.0% to 5.8%
TMYx(2004-2018)	-4.5% to +7.8%	+1.4% to 6.0%
TMYx(2007-2021)	-2.1% to +10.5%	+1.5% to 6.4%

Results of Heating and Cooling Load. The analysis of heating and cooling energy consumption from 1970 to 2021 reveals a discernible trend in energy usage patterns. Heating energy consumption exhibited fluctuations within this period, with a notable peak of 4,646,162 kBtu in 1978 and a significant reduction to 1,947,067 kBtu in 2017. Conversely, cooling energy consumption demonstrated an upward trajectory, escalating from 3,657,171 kBtu in 1976 to 4,825,670 kBtu in 2017. This divergent trend is further substantiated by the time series analysis, which indicates a substantial decline in heating energy consumption concurrent with a decrease in Heating Degree Days (HDD), as illustrated in Figure 15. In contrast, cooling energy consumption, along with Cooling Degree Days (CDD), has shown a consistent increase over the same timeframe, as depicted in Figure 16.

Projections for future heating and cooling energy consumption indicate a continuation of these trends, with significant deviations from historical patterns observed from 1970 to 2021. Predictive models suggest a reduction in heating loads by 21% to 23.3% in the mid-21st century (2026-2045) and by 46.1% to 50.3% towards the end of the century (2080-2099), as shown in Figure 17. Conversely, cooling energy consumption is projected to rise by 17.6% to 18.8% in the mid-21st century and by 46.5% to 49.2% by the late 21st century, as evidenced in Figure 18.

Conclusion

The analysis references the accuracy of various Typical Meteorological Year (TMY) weather files in reflecting long-term climate patterns using statistical methods. Findings suggest that TMY weather files tend to omit extreme weather events, leading to a narrower data range compared to the original, longer-term climatic records. TMY3 data most closely mirrors the long-term averages.

It is noted that TMY weather files generally do not perform well in representing solar radiation, and none is deemed suitable for wind studies. It was concluded that

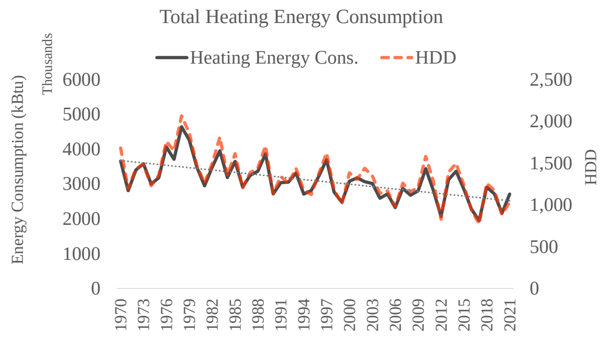

Figure 15 Time-series Plot of Heating Energy Consumption from 1970 to 2021

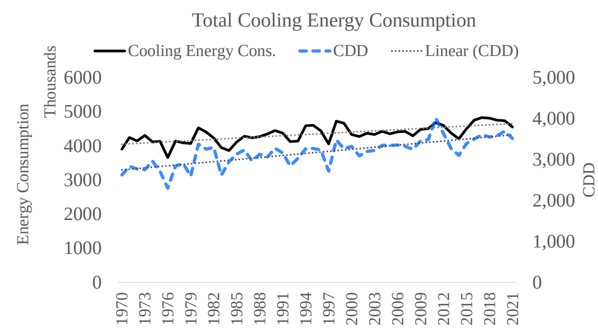

Figure 16 Time-series Plot of Heating Energy Consumption from 1970 to 2021

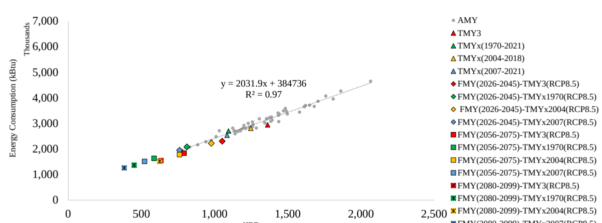

Figure 17 Heating Energy Consumption by HDD

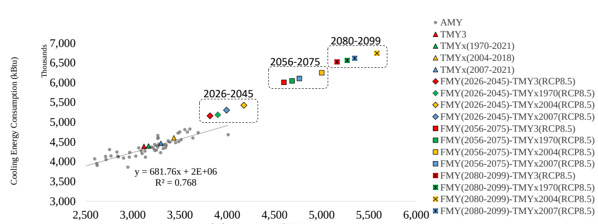

Figure 18 Cooling Energy Consumption by CDD

assigning weighting factors significantly impacts the final ranking for selecting typical months (TMM).

Moreover, energy consumption results shows that all models using TMY weather files underestimate actual energy usage. Although the TMY3 weather file is found to be the closest to the long-term average for most weather indices, the energy model using the TMYx(2004-2018) weather file shows the most proximate result to the average energy consumption from 1970 to 2021 (+0.2% difference). Results indicated a slightly increasing trend in cooling energy consumption and a sharp decrease in heating energy usage from 1970 to 2021. Future climate projections suggest a continuation of these trends, with total energy consumption potentially increasing between 0.8% in the mid-21st century and 6.4% by the late 21st century.

Despite their usefulness in many building analyses, TMY files may fall short in capturing the full complexity of future climatic conditions and extreme weather events. It is recommended that building professionals exercise caution when using TMY files for future-oriented building analyses and consider incorporating additional data and methods to encompass a wider array of climate scenarios.

The study recommends adoption of multi-year energy simulation analyses along with future climate projection data in architectural decision-making processes. Relying on single-year models can overlook the natural variability of climate over time and may lead to underestimations of future energy demands. Nonetheless, energy projections based on future climate data fall within the historical range of energy consumption recorded from 1970 to 2021, underscoring their potential reliability.

Limitations

The scope of this study was confined to the examination of four typical-year weather files, each developed in accordance with the TMY/ISO 15927-4:2005 methodology. The investigation focused exclusively on the building energy performance of a representative secondary school located in Houston, Texas. It's important to note that the study did not extend to other performance metrics or climate zones, nor did it encompass a variety of building types. Consequently, the findings are not necessarily generalizable to different settings or to the performance of buildings with distinct functions or designs. This specificity in the study's design delineates the boundary for the applicability of its results and suggests avenues for future research to explore the influence of other climate zones, building types, and performance metrics.

Nomenclature

BPS= Building Performance Simulation

CDF = Cumulative Distribution Function

FS = Finkelstein-Schafer (FS) index

TMY= Typical Meteorological Year

AMY = Actual Meteorological Year

FMY = Future Meteorological Year

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