Impact of Typical-year and Multi-year Weather Data on The Energy Performance of The Residential and Commercial Buildings

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Abstract

Changes in the weather patterns worldwide and global warming increased the demand for high-performance buildings resilient to climate change. Building Performance Simulation (BPS) is a robust technique to test, assess, and enhance energy efficiency measures and comply with stringent energy codes of the buildings. Climate has a considerable impact on the buildings' thermal environment and energy performance; therefore, choosing reliable and accurate weather data is crucial for building performance evaluation and reducing the performance gap. Typical Weather Years (TWYs) have been traditionally used for energy simulation of buildings. Even if detailed energy assessments can be performed using available multi-year weather data, most simulations are carried out using a typical single year. As a result, this fictitious year must accurately estimate the typical multi-year conditions. TWYs are widely used because they accelerate the modeling process and cut down on computation time while generating relatively accurate long-term predictions of building energy performance. However, there is no certainty that a single year can describe the changing climate and year-by-year variations in weather patterns. Nowadays, with increased computational power and higher speeds in calculation processes, it is possible to adopt multi-year weather datasets to fully assess long-term building energy performance and avoid errors and inaccuracies during the preliminary selection procedures.

This study aims to investigate the impact of Typical Weather Years and Actual Weather Years (AWYs) on a single-family house and a university building under two opposite climates, Winnipeg (cold) and Catania (hot). First, a single-family house in Winnipeg, Canada, was selected to evaluate how typical weather years affect the energy performance of the building and compare it with AWYs simulation. Two widely used typical weather data, CWEC and TMY, were selected for the simulation. The results were compared with the outcomes of simulation using AWYs derived from the same weather station from 2015 to 2019, which covered the latest climate changes. The results showed that typical weather years could not sufficiently capture the year-by-year variation in weather patterns. The typical weather years overestimated the cooling load while underestimating the heating demands compared to the last five actual weather years. A more extensive study was conducted for more confidence in the findings and understanding of the weather files. The research was expanded by comparing the results of building performance simulation of the single-family house and an institutional building with more complex envelope characteristics belonging to the University of Manitoba under cold (Winnipeg, Canada) and hot (Catania, Italy) climates. Overall, 48 simulations were performed using ten actual weather years from 2010 to 2019 and two TWYs from each climate for both buildings. The results showed that while the TWYs either overestimate or underestimate the cooling and heating demands of both buildings, cooling load predictions were highly overestimated in the heating-dominant climate of Winnipeg, ranging from 10.5% to 82.4% for both buildings by CWEC and TMY weather data. In the cooling-dominant climate of Catania, energy simulations using IWEC and TMY typical weather data highly overestimated the heating loads between 2.8% and 82.4%.

Acknowledgments

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Last but not least, I would like to give special thanks to my beloved parents and elder brother, to whom this dissertation is dedicated to having been a constant source of love, concern, support, and strength.

Contribution of Authors

1. **Amir Moradi, Miroslava Kavgic (IBPSA eSim Conference paper)**

Impact of typical-year and multi-year weather data on the energy performance of the residential building

   a) Amir Moradi: Edited and developed the ideal load air system for the residential building model, gathered weather data, performed data analysis of simulation, and wrote the paper
   b) Miroslava Kavgic: Suggested and supervised this research, analyzed data and assisted with the writing and editing of the paper

2. **Amir Moradi, Miroslava Kavgic, Vincenzo Costanzo, Gianpiero Evola (Journal of Applied Energy)**

Typical-year and multi-year weather data in building performance simulations: the role of climate and building typology on energy predictions

   a) Amir Moradi: Edited and created new operational schedules and internal loads for models, developed the ideal air load system for the house model, performed data analysis of simulation, and wrote the paper
   b) Miroslava Kavgic: Suggested and supervised this research, analyzed data and assisted with the writing and editing of the paper
   c) Vincenzo Costanzo (Assistant Professor at University of Catania): Suggested the charts, reviewed and edited the paper
   d) Gianpiero Evola (Associate Professor at University of Catania): Suggested the charts, reviewed and edited the paper

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Abbreviations and Acronyms

Acronym	Definition
ASHRAE	American Society of Heating, Refrigerating, and Air-Conditioning Engineers
AWY	Actual Weather Year
BLAST	Building Loads Analysis and System Thermodynamics
BPS	Building Performance Simulation
CIBSE	Chartered Institution of Building Services Engineers
CWEC	Canadian Weather for Energy Calculations
CWEED	Canadian Weather Energy and Engineering Datasets
DOE	Department of Energy
DSY	Design Summer Year
EPW	Energy Plus Weather file
GHG	Green House Gas
HVAC	Heating, ventilation, and air conditioning
IDF	Input Data File
IEA	International Energy Agency
IEO	International Energy Outlook
IWEC	International Weather for Energy Calculations
MNECB	Model National Energy Code for Buildings
NCDC	National Climate Data Centre
NECB	National Energy Code of Canada for Buildings
NRC	National Research council
NREL	National Renewable Energy Laboratory
NZEB	Net Zero Energy Buildings
PASSYS	Passive Solar Components and Systems Testing
PCM	Phase Change Material
TMM	Typical Meteorological Months

TMY	Typical Meteorological Year
TRY	Test Reference Year
TWY	Typical Weather Year
UMY	Untypical Meteorological Years
WYEC	Weather Year for Energy Calculations
XMY	Extreme Meteorological Year

1 Introduction

Over the last two decades, the rapid growth of global energy consumption has raised concerns about various negative environmental consequences, such as global warming, ozone layer depletion, air pollution, biodiversity loss, and deforestation. Anthropogenic global warming is the world's foremost ecological disaster currently. The leading cause has been identified as the constantly rising greenhouse gas (GHG) emissions mainly associated with fossil fuel consumption (Li & Yao, 2009). According to The International Energy Outlook (IEO), the global use of marketed energy will experience a 48% increase between 2012 and 2040 (Conti et al., 2016). Also, the building and construction section, including commercial, institutional, and residential buildings, accounts for a significant share of global final energy consumption (35%) and energy-related CO2 emissions (39%) (IEA, 2019). Enhancing the energy efficiency of buildings is a significant element of accomplishing more sustainable energy management (Rouleau et al., 2018). To address this worldwide issue, policymakers are attempting to implement energy-efficient solutions, as energy efficiency has been found to be the most cost-effective and readily accessible method of reducing carbon emissions (Akbari et al., 2016). As a result, building sector stakeholders, such as the American Society of Heating, Refrigerating, and Air-Conditioning Engineers (ASHRAE) and the European Performance of Buildings Directive (EPBD), are establishing goals to produce market-viable Net Zero Energy Buildings (NZEB) (Hermelink et al., 2013).

Building codes play a crucial role in setting standards for energy performance and are becoming more stringent worldwide to reduce the long-term energy demand of the built environment (Golove & Eto, 1996; May & Koski, 2007). National Research, for instance, investigated and developed guidelines for designing high-performance buildings in terms of energy and included a set of energy efficiency suggestions in the Model National Energy Code for Buildings (MNECB), 1983. These standards have been improved and updated in every version until they led up to the latest National Energy Code of Canada for Buildings (NECB), 2020.

Architects, building scientists, and engineers need to investigate various design approaches and advanced technologies to meet these high-performance requirements. Also, a thorough understanding of building physics is needed since improving design becomes more challenging as buildings become more energy efficient (Rouleau et al., 2018). Buildings are a series of sophisticated systems. Various factors, such as ambient weather conditions, heat transfer through the envelope, air circulation strategies, passive systems, internal gains, solar radiation, and occupants' behavior, contribute to their energy performance. Building Performance Simulation (BPS) is an approach that allows testing, analyzing, and optimizing energy-efficient measures and advanced systems (Al-janabi et al., 2019; Dutta & Samanta, 2018; Korolija et al., 2013; Mousa et al., 2017). Furthermore, the performance-based approach is a crucial enabler of rational decision-making, design solutions, and compliance with energy code (Hensen & Lamberts, 2012). Whole-building energy simulation tools are essential in predicting building energy performance as they offer users key indicators such as energy consumption, carbon emissions, indoor environmental quality, and costs (D. B. Crawley et al., 2008). The whole building energy simulation tool also allows the users to evaluate the building under a specific scenario (Augenbroe et al., 2004). Over the last 60 years, building energy modeling developers have provided hundreds of building energy programs and have enhanced their reliability (D. B. Crawley et al., 2008). Nevertheless, since building energy modeling became integrated into the building design and compliance processes with energy codes, the energy performance gap remains one of the most discussed concerns in the design community. The building performance gap can be described as a mismatch between the predicted energy performance of buildings and actual measured performance. since building energy modelling became integrated into the building design and compliance processes with energy codes, the energy performance gap remains one of the most discussed concerns in the design community. Although it seems sensible to expect some difference in prediction models and measurements because there is always uncertainty in predictions and scattered data in measurements, the gaps are too large to be considered normal (Zhao & Magoulès, 2012). In this respect, several studies showed that the weather files used for the simulations are a significant source of uncertainties due to considerable impacts on the model predictions (Cui et al., 2017; Evola et al., 2021; Hopfe & Hensen, 2011; Yang et al., 2007). Also, ongoing changes in our climate and the limitations in observations, such as unsuitable station configuration or placement, poor station maintenance, erroneous instrument reading, or inaccurate data digitization and post-processing, impact the reliability of weather data for building energy simulations (Brönnimann, 2015; *Report on Climate Change and Land*, n.d.). Thus, choosing appropriate weather files is critical for precise and accurate model predictions. The most commonly used form of weather data for building simulations is the Typical Weather Year (TWY), which contains 8760 hourly values of meteorological parameters derived from a long-term database through statistical processing in a one-year sequence. The American Society of Heating, Refrigerating, and Air-Conditioning Engineers (ASHRAE) first proposed this approach in the 1970s to examine building energy demand for air conditioning (ASHRAE, 1989). In this regard, ASHRAE compiled yearly weather datasets for several locations in the U.S. using a filtering procedure that discards years with extremely high or low air temperatures to develop the so-called Test Reference Year (TRY) (NCDC, 1976). As a result, the TRY typifies an exceptionally mild year and does not sufficiently represent the long-term weather variability for a given site. Also another major flaw of the TRY procedure is the lack of solar data and using cloud cover and cloud type for estimating the amount of solar radiation. A Typical Meteorological Year (TMY) consisting of 12 typical meteorological months selected from various calendar months of a multi-year weather database became a preferred alternative to TRY and the standard weather data format for building performance simulations. The twelve months, typically taken from different years of record, are then concatenated by smoothing discontinuities through curve-fitting techniques to create an entire year. There are various methods for forming a TMY, such as the Sandia method (I. J. Hall et al., 1979), the Danish method (Lund & Eidorff, 1981), the Crow method (Crow, 1984), and the Festa-Ratto method (Festa & Ratto, 1993). The Sandia method, which was initially developed in 1978 by Hall et al., is currently one of the most used approaches by the building energy simulation community. The National Renewable Energy Laboratory (NREL) recently updated this method into formats referred to as TMY2 in 1995 (Marion & Urban, 1995) and TMY3 in 2005 (Wilcox & Marion, 2008a). Typical Weather Years (TWY) became widely used because they simplified the modeling process and reduced computational time while producing reasonably accurate predictions of building energy performance in the long term. Nevertheless, the use of TWY brings about some critical issues. First, a typical year built upon historical data might not represent the present-day climate conditions, especially considering climate change. For example, Radhi reported that using a TWY based on data from 1961 to 1990 underestimated the electricity consumption in a central all-air Heating, ventilation, and air conditioning (HVAC) system by approximately 14.5% for low-rise and high-rise commercial buildings in Bahrain compared to the predictions obtained using weather data from 1992 to 2005 (Radhi, 2009). The use of outdated weather files is particularly problematic for some parts of the world, such as Canada, which warms up at approximately twice the global average (Climate Change Canada, 2019). For instance, (Kočí et al. (2019) investigated the energy demands using current weather data sets from 2014 to 2017 compared to the test reference year synthesized from the weather data between 1991 and 2005. The simulation results support the warming trend from 2013 to 2017, with heating demands 3.95% below the average and cooling demands 3.96% above the average compared with the Test Reference Year. Second, a typical year is inappropriate for designing technical systems or sizing equipment because it omits worst-case scenarios, i.e., extreme cold or hot weather conditions (D. B. Crawley & Lawrie, 2015). Third, TWY developed through different methods exisitng in the literature might lead to diverging energy simulation outcomes (Bhandari et al., 2012a; Skeiker, 2007; Sorrentino et al., 2012), thus affecting the design decisions (Bevilacqua et al., 2019; Pernigotto et al., 2017). Last but not least, a TWY cannot adequately reflect the fluctuations due to the actual year-by-year variability in the weather conditions (D. Crawley, 1998). Therefore, a new approach to building performance simulation requires replacing a single-value energy prediction with the range that realistically represents building performance over various weather conditions. Recent improvements in computational power allowed overcoming these hurdles through multi-year simulations with Actual Weather Years (AWYs), whose outputs reflect the building's response to the actual year-by-year variation in the climate conditions through an extended period. As a result, all energy use variations can be considered for optimal decision-making and avoid a preliminary selection procedure that may introduce errors or inaccuracy (D. Crawley, 1998). Presently, a limited number of research studies investigated the advantages of using the Actual Weather Years approach instead of the Typical Weather Year. One of the first studies (D. Crawley, 1998) showed that energy consumption in eight different office spaces in the U.S varies between -11% to 7% in the 30-year actual weather data set compared to the multi-year weather dataset. Cui et al. draw similar conclusions but with even a higher range of variation for the single-year results for a medium-sized office building in ten different cities in China (Cui et al., 2017). More recently, Evola et al. used multi-year and typical-year approaches to investigate the energy use of an office building and a residential building in Sicily, Italy. They discovered that TWY resulted in 10-35% and 15-25% underestimation in selecting the appropriate heating and cooling systems size (Evola et al., 2021).

Based on the results, local weather considerably affects the construction and performance of the building. Good quality weather data is critical for building performance simulation. Designers should hesitantly select the appropriate weather data.

1.1 Objectives and contributions to the field

The primary aim of this thesis has been to investigate and compare the impact of different weather datasets (AWYs and TWYs) on the energy performance of commercial and residential buildings with distinct characteristics and technical system features under cold Canadian and Mediterranean climates. Furthermore, it also investigated the implication of different setpoints on the simulation results. In this respect, setpoints appropriate for cold and warm weather conditions were investigated. The following objectives have been undertaken to achieve this aim:

1) To perform an analysis on the energy performance and distinguish the TWYs with more reliable results for each climate and each building
2) To indicate the most influential weather parameters on each type of the buildings
3) To simulate the buildings using each of the gathered weather datasets and compare the buildings' performance under selected climates
4) To develop an ideal load air system for the residential and commercial building energy models using EnergyPlus
5) To set new operational schedules and loads for buildings considering both climates
6) To select the nearest weather station with the reliable required data for the energy simulation in Winnipeg, Manitoba, Canada
7) To select a hot and Mediterranean climate (Catania, Sicily, Italy) and weather station with reliable data for AWYs and TWYs datasets

This study aims to extend the current understanding in applying different weather datasets for energy simulations and compare the impact of these weather datasets on the energy performance of two distinct building types. Thus, to the best of the authors' knowledge, this is the first study to compare the impact of typical single-year and multi-year-by-year weather datasets on the building energy performance under two distinct climates with an extreme need for heating and cooling. Furthermore, unlike similar studies, it investigated two very different building types a complex high-performance university building and a typical single-family house.

1.2 Thesis structure

This thesis consists of the following chapters:

Chapter 2 provides a comprehensive overview of Building Performance Simulation (BPS) and outlines past studies in the fields of energy modeling and its limitation. Chapter 2 also discusses using the EnergyPlus simulation tool, related studies, and limitations. In addition, this chapter provides an overview and background of weather data, their implementation in building energy simulation, and how they affect the prediction of the energy performance of buildings.

Chapter 3 is a paper-styled chapter that investigates the impact of two widely used TWYs of Winnipeg, Canada, and compares it with actual weather data from 2015 to 2019 on a conventionally constructed typical single-family house using setpoints often used for Canadian climatic conditions.

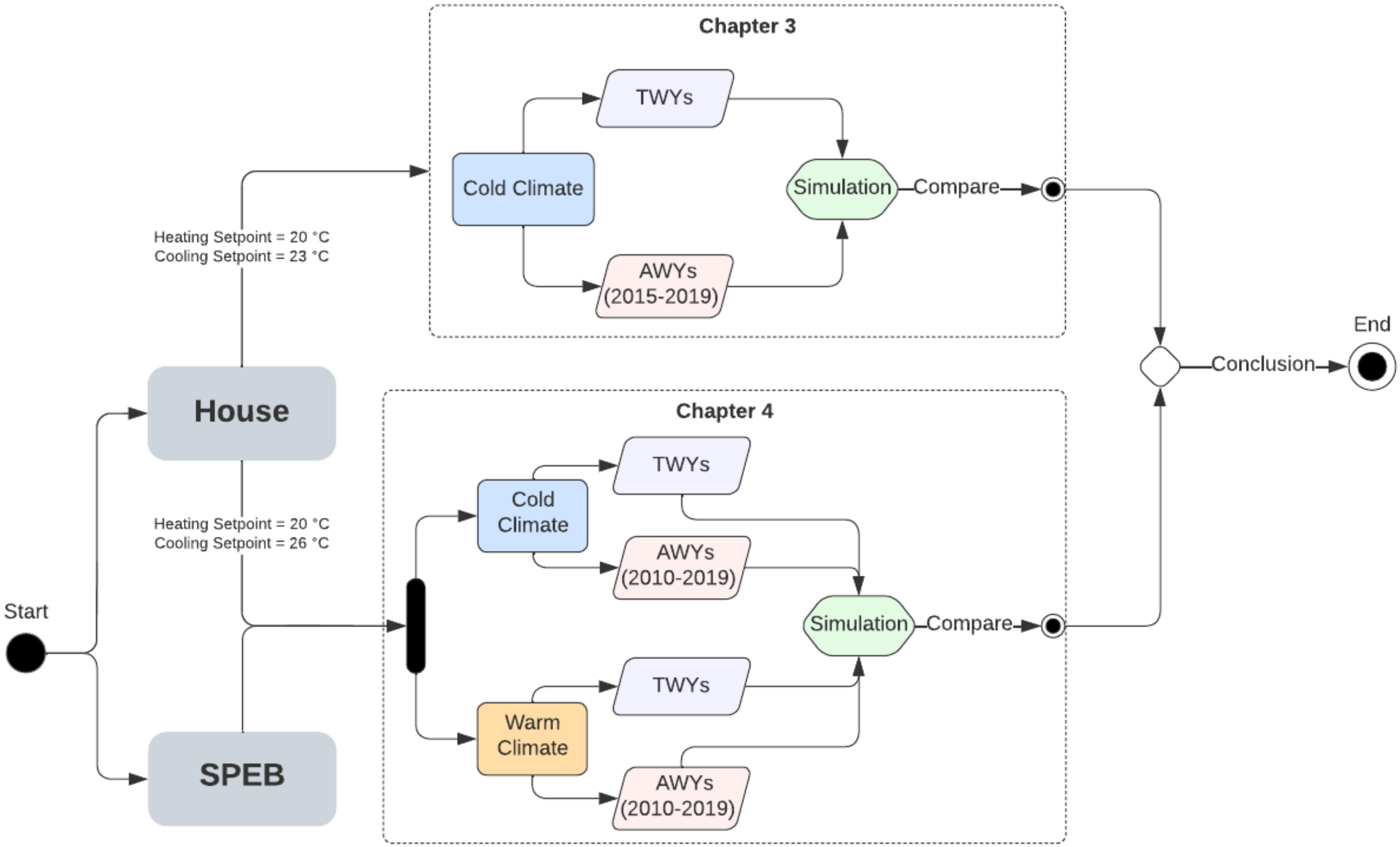
Chapter 4 is a paper-styled chapter that expands the previous study in chapter 4 and evaluates and compares the use of last decade AWYs and the most common TWYs datasets for building performance simulation for two types of buildings under cold and warm climatic conditions, namely Winnipeg, Canada and Catania, Italy. Also, this chapter seeks to extend the knowledge about the limitations and advantages of using TWYs and AWYs in building energy simulation based on the building type scenarios. Moreover, it further explores the impact of weather files on the simulation outputs by using building models with cooling and heating setpoints different from *Chapter 3* appropriate for both warm and cold climates. Furthermore, this chapter investigates the single-family house with a more energy-efficient lighting system and reduced internal heat gains than *Chapter 3*.

Chapter 5 provides conclusions of both studies in chapters 3 and 4, conducted in different contexts. Also, this chapter points out the limitations and recommendations for future research.

1.3 Research Methodology

The methodology of this thesis begins with investigating the impact of TWYs and AWYs on the energy performance of a typical conventional single-family house under the cold climate of its original location in Winnipeg, Manitoba, Canada. For this aim, the energy model of the house is developed in EnergyPlus, and the ideal air load system with appropriate setpoints for Canadian locations is selected for the simulation. The two most common typical weather data of CWEC and TMYx(15) and actual weather year data from 2015 to 2019 are derived from the Fork weather station, which is in the vicinity of the case study for the energy simulation.

Then the study expanded by including the energy model of the Stanley Pauley Engineering Building, located in Winnipeg, Manitoba, and the weather data from the hot climate of Catania, Italy, in energy simulations of both buildings. The new setpoints for residential buildings are modified to be more appropriate for both climates of Winnipeg and Catania. The Italian weather data have been provided by the weather station owned by SIAS (Sicilian Agrometeorological Information System), situated 3 km south of the Fontanarossa airport in Catania. TMY (first original version, also known as Sandia's method; Hall et al., 1979) and IWEC, two of the most recent and widely used TWYs datasets, were chosen for both locations, resulting in four datasets: CWEC (Canada), which covers the 1998–2017 period; IWEC (Italy), which contains the 2002–2019 period; and TMYx(15) for Canada and Italy. The selected Actual Weather Year data period is from 2010 to 2019 based on data availability over a ten-year timeframe. This time frame was chosen because of the significant global climatic changes that have occurred over the past ten years. Page 11 shows the flow chart of the research methodology.


Chapter 3
TWYs
Cold Climate
Simulation
Compare
AWYs
(2015-2019)
Heating Setpoint = 20 °C
Cooling Setpoint = 23 °C
End
Conclusion
House
Chapter 4
TWYs
Cold
Climate
AWYs
(2010-2019)
Heating Setpoint = 20 °C
Cooling Setpoint = 26 °C
Start
Simulation
Compare
TWYs
Warm
Climate
AWYs
(2010-2019)
SPEB

2 Literature review

This chapter provides a review of building performance simulation, a comprehensive analysis of the previous work conducted in the field of energy modeling, and the impacting factors of the energy gap. Also, this chapter presents a background of EnergyPlus as a building performance simulation tool and its implementation in various studies. Moreover, it discusses different weather data used in building performance simulation tools as boundary conditions, their impact on the simulation results, and their role as one of the main factors of building performance gaps.

2.1 Building performance simulation

Building performance simulation has become an essential aspect of buildings' design process and ensures compliance with energy codes and requirements. Also, dynamic processes, like climate change, depletion of non-renewable energies, growing needs and expectations of occupants' thermal comfort, and improved concern of the link between the indoor environment and the occupants' well-being are some of the challenges that researchers and designers should take into account for designing sustainable buildings. Addressing these factors and developing robust building and system solutions to sustain future demands mandates an integrated sub-system approach, Figure 1. (Hensen & Lamberts, 2012).

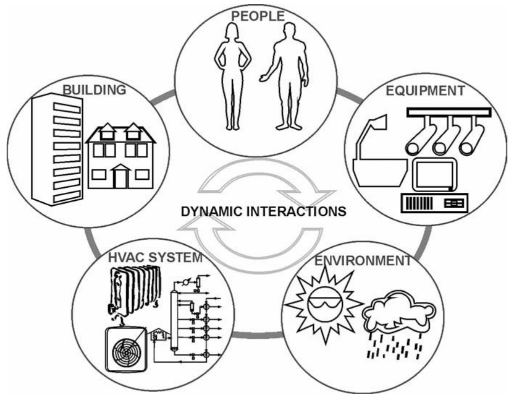


Figure 1: Dynamic interactions of sub-systems in building (Hensen & Lamberts, 2012).

Historically, design tools, such as EnergyPlus and IES, have been built by reducing the complexity of the underlying system equations to reduce the computational load and the resulting input burden on the user. Some aspects of the system, like longwave radiation exchange, might be overlooked within a simulation tool, or simple boundary conditions, such as steady-state or steady cyclic, may be implemented. A mathematical model in the building simulation tool represents each possible energy flow path and its interactions. Simulation, in this perspective, is an attempt to resemble reality (Clarke, 2001). A building energy model is a simulation tool that calculates buildings' thermal loads and energy consumption by including the impact of all of the sub-systems in the simulation. The building energy model is typically used in designing new buildings or renovating existing buildings. Building energy models have been used since 1980 (Mills, 2004; Ryan & Sanquist, 2012; Swan & Ugursal, 2009) and have been developed and enhanced throughout the years to model more sophisticated and detailed models. Hundreds of building performance simulation tools have been developed, refined, and used over the last 50 years. The building energy modeling tools have appeared in the market as free (e.g., EnergyPlus, OpenStudio, eQuest, Energy3D) and commercial (e.g., TRNSYS, IES) programs with varying graphical capabilities, precision, versatility, user-friendliness, simulation duration, life-cycle application, and price. Since the development of Building energy modeling tools, they have been used for simulating and analyzing buildings as a whole structure, complex HVAC systems (Al-janabi et al., 2019), and energy-saving methods of the buildings' material and components like shading devices, windows, and opaque surfaces (Al-Janabi & Kavgic, 2019; P. Loutzenhiser et al., 2009; P. G. Loutzenhiser et al., 2007).

2.1.1 Energy Performance gap

Energy simulation tools allow researchers and designers to predict variables to help them decide the best strategy to save cost and energy and increase thermal comfort. However, the energy performance gap is one of the most significant concerns, and acquiring accurate simulation models that match the actual building is challenging for the design community (Figueiredo et al., 2018). According to several studies, design assumptions are the most discussed cause of the performance gap (de Wilde, 2014; Menezes et al., 2012b). Many characteristics of the building's functions are uncertain during the design stage and will be based on the designer's expertise. Hence, there will be an oversimplification in data inputs regarding the built quality (Menezes et al., 2012b). Dwyer (2013) also pointed out that the knowledge and skill in using simulation tools will determine how close the results are to the actual construction. In a study by Polly et al. (2011), Inaccuracies in the mathematical modeling of the building's and its equipment's physical behavior (physics algorithm) and Inadvertently introduced typographical and logic flaws within program codings (coding errors) are two software errors that affect the predictions of the building simulation. Various studies investigate and compare the features and capabilities of different BPS (Attia & Herde, 2011; D. Crawley et al., 2000). Also, some studies evaluated the predictions of BPS tools under different zone distributions and complexity of the case study. For instance, Waddell & Kaserekar (2010) and Zhu et al. (2013) used a single zone to evaluate the difference in software calculations.

Abdullah et al. (2014) examined and simulated the energy usage of a newly constructed and occupied research laboratory building located in Tacoma, Washington, in two separate early energy analysis software (Vasari/GBS and Sefaira), and compared it to the actual measured energy consumption. Andolsun & Culp (2008) compared EnergyPlus with DOE-2 by simulating several case studies starting from a sealed box without infiltration and internal loads and extending it to a more complex building. Another significant stage that causes the performance gap is the construction phase. Many studies, including industry reports and publications evaluating various scales and types of case studies, have found that on-site construction quality frequently differs from design standards (Imam et al., 2017). Gaps in insulation, thermal bridging, and airtightness are frequent but rarely considered when predicting energy use (de Wilde, 2014; Menezes et al., 2012b). Uncertainties related to physical properties can be identified and quantified with measurements and tests, improving the model's quality assurance. Began in 1985, the European PASSYS Project (Passive Solar Components and Systems Testing) is an effort to increase confidence in the adoption of energy-efficient and passive solar building materials and the evaluation procedures used to provide beneficial thermal performance properties of such products. However, besides the steady-state evaluation of PASSYS, it became clear that dynamic testing required high-quality performance characteristics for building components tested in actual climates. The PASLINK is an upgrade version of PASSYS that improves the measurement accuracy by implementing the calibration of instrumentation and the test cells and data processing and analysis (Baker & van Dijk, 2008). For example, in a study by Leal & Maldonado (2008), a prototype of the SOLVENT window was installed in the PASLINK test cell to collect experimental data that helped develop models for the simulation of the component its integration in the global simulation of the building.

Besides, the operational stage of a building is frequently highlighted as a significant cause of discrepancy with design stage predictions. Occupants' behavior is often emphasized in studies on the performance gap during the operation phase (de Wilde, 2014; Haldi & Robinson, 2008; Menezes et al., 2012b). Even in fully automated buildings, occupants can influence their energy usage by affecting internal conditions, such as opening windows blocking air inlets/outlets (Demanuele et al., 2010). Furthermore, a significant portion of the energy is related to the facilities managers (FM), which control central plant equipment. According to Bordass et al. (2001), Inappropriate tactics might result in excessive energy waste, whereas good management and controls can efficiently operate the building services.

Hopfe & Hensen (2011) divided the uncertainty analysis in building performance into three types, namely: design, physical and scenario uncertainties. As indicated in referred studies, uncertainty in the design arises from changes between the design and construction stages, and physical properties account for the most physical uncertainties. Uncertainty in the scenario, also known as uncertainty in boundary conditions, is sub-divided into external and internal scenarios uncertainties. Internal uncertainties include heat gains from occupants, equipment, lighting, and various setpoints, and external uncertainty are weather data and climate change.

2.2 EnergyPlus

Numerous widely used building energy simulation programs worldwide are evolving, with some employing simulation methods (and even code) developed in the 1960s. With advances in analysis techniques and increased computational power, these programs have improved significantly and are more comprehensive. EnergyPlus has its roots in both the BLAST and DOE–2 programs. BLAST (Building Loads Analysis and System Thermodynamics) and DOE–2 were developed and released in the late 1970s and early 1980s as energy and load simulation tools (DOE, 2009). The main objective of developing BLAST and DOE-2 was to help architects and design engineers who want to size the HVAC equipment, develop retrofit options for LCC (Life Cycling Cost) analysis, and optimize the energy performance of the building (DOE, 2009). EnergyPlus, like its predecessors, is an energy analysis and thermal load simulation program developed for simulating buildings with all their related design features, such as building physical components, heating, ventilating, and air conditioning equipment (D. B. Crawley et al., 2001).

EnergyPlus has been developed using the Fortran90 coding language and includes structured, modular code that is simple to maintain, update and extend (D. Crawley et al., 2000). Figure 2 presents the overall program structure and the three primary components: Simulation Manager, Heat Balance Simulation module, and Building Systems Simulation module.

The Simulation Manager manages the overall simulation process. At the same time, the Heat Balance Simulation module calculates thermal and mass loads. The Building Systems Simulation

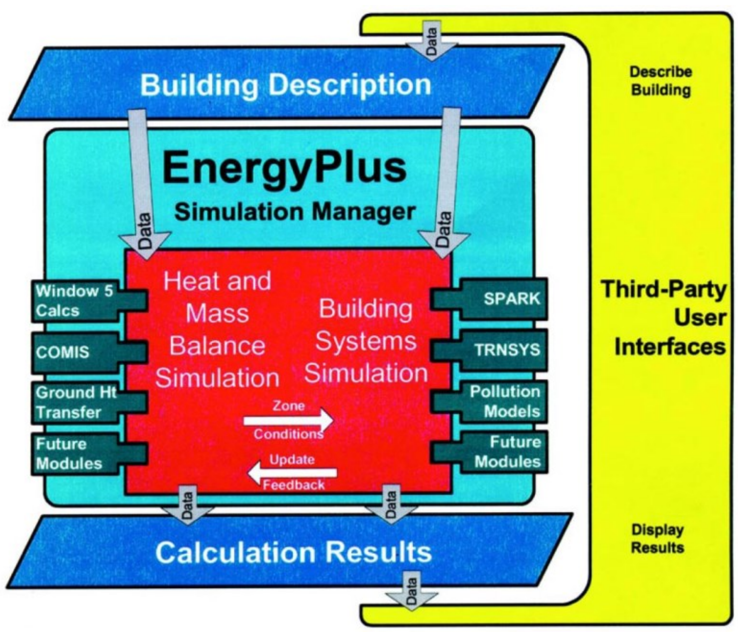


Figure 2: overall energyplus structure (DOE, 2009)

Manager handles communication between the heat balance engine and the HVAC water and air loops and their associated components (D. Crawley et al., 2000).

EnergyPlus is a program that uses two primary input data for producing the outputs files, which are accessible through the EP-Launch (figure 3):

- IDF (The Input Data File): the IDF contains all the data in a text file that describe the building and HVAC system to be simulated.
- EPW (Energy Plus Weather file): EPW formats are text-based comma-separated CSV files and include metadata, such as site location, elevation, and time zone. They also contain column headings with the required weather variables. The structure of the epw format was developed by DOE and is compatible with more than 20 building simulation tools such as ESP-r, IES, and TAS. According to the bi-annual publications of the International Building Performance Simulation Association (IBPSA), EnergyPlus is the most common energy

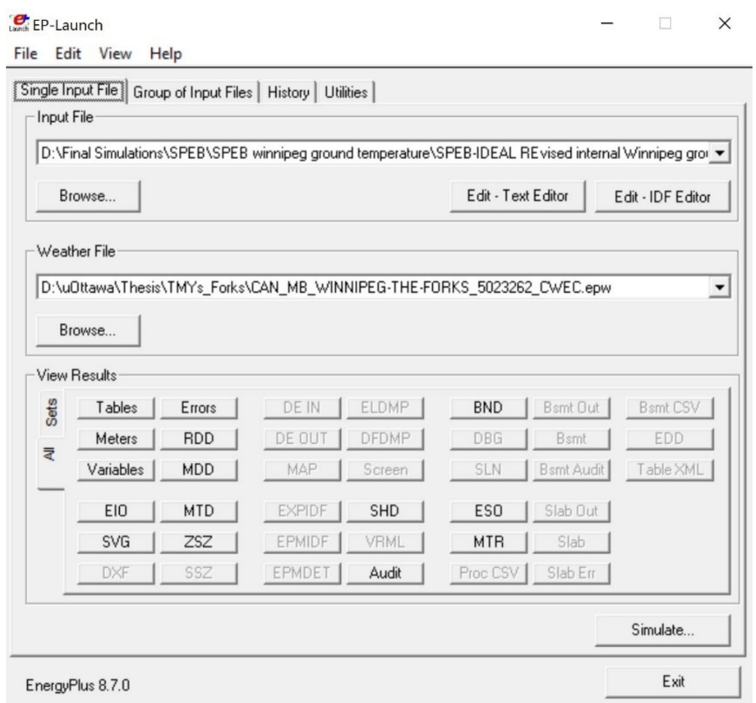


Figure 3: The EP-Launch window screen

simulation tool. As a result, EnergyPlus's prominence has contributed to popularizing its native weather file format, the 'epw' file. Figure 4 shows the header of an epw format of a weather file that provides information about the location and the weather data format, which is TMY.

```
1  LOCATION,Winnipeg The Forks,MB,CAN,ISD-TMYx,715790,49.88830,-97.12950,-6.0,230.0
2  DESIGN CONDITIONS,1,2017 ASHRAE Handbook -- Fundamentals - Chapter 14 Climatic Design Information,,Heating,1,-28.3,
3  TYPICAL/EXTREME PERIODS,6,Summer - Week Nearest Max Temperature For Period,Extreme,7/22,7/28,Summer - Week Nearest
4  GROUND TEMPERATURES,3,.5,,,,-9.20,-10.58,-8.13,-4.29,5.74,13.49,18.71,20.30,17.59,11.58,3.54,-3.91,2,,,,-4.11,-6.5
5  HOLIDAYS/DAYLIGHT SAVINGS,No,0,0,0
6  COMMENTS 1,"NCEI ISD - #years=[15] Period of Record=2004-2018; Jan=2015; Feb=2009; Mar=2017; Apr=2017; May=2017; J
7  COMMENTS 2,"Downloaded from Climate.Onebuilding.org -- Ground temps represent undisturbed earth temperatures - cal
8  DATA PERIODS,1,1,Data,Sunday,1/ 1,12/31
9  2015,1,1,1,60,?9?9?9?9E0?9?9?9?9?9?9?9?9?9?9?9?9*9*9*9*9*9,-4.5,-8.7,70,97678,0,0,253,0,0,0,0,0,0,0,290,2.1,9,9,77
10 2015,1,1,2,60,?9?9?9?9E0?9?9?9?9?9?9?9?9?9?9?9?9*9*9*9*9*9,-4.4,-9.1,67,97650,0,0,260,0,0,0,0,0,0,0,310,2.1,10,10,
11 2015,1,1,3,60,?9?9?9?9E0?9?9?9?9?9?9?9?9?9?9?9?9*9*9*9*9*9,-8.8,-11.3,80,97788,0,0,221,0,0,0,0,0,0,0,20,3.1,5,5,77
12 2015,1,1,4,60,?9?9?9?9E0?9?9?9?9?9?9?9?9?9?9?9?9*9*9*9*9*9,-10.1,-13.0,77,97899,0,0,216,0,0,0,0,0,0,0,30,3.1,5,5,7
13 2015,1,1,5,60,?9?9?9?9E0?9?9?9?9?9?9?9?9?9?9?9?9*9*9*9*9*9,-10.8,-13.8,76,98018,0,0,213,0,0,0,0,0,0,0,20,2.6,5,5,7
14 2015,1,1,6,60,?9?9?9?9E0?9?9?9?9?9?9?9?9?9?9?9?9*9*9*9*9*9,-11.1,-14.3,75,98092,0,0,211,0,0,0,0,0,0,0,20,2.1,5,5,7
15 2015,1,1,7,60,?9?9?9?9E0?9?9?9?9?9?9?9?9?9?9?9?9*9*9*9*9*9,-12.6,-17.1,66,98211,0,0,196,0,0,0,0,0,0,0,360,4.1,1,1,
16 2015,1,1,8,60,?9?9?9?9E0?9?9?9?9?9?9?9?9?9?9?9?9*9*9*9*9*9,-15.6,-19.8,67,98342,0,0,185,0,0,0,0,0,0,0,360,3.6,1,1,
17 2015,1,1,9,60,?9?9?9?9E0?9?9?9?9?9?9?9?9?9?9?9?9*9*9*9*9*9,-16.5,-20.7,67,98477,0,0,182,0,0,0,0,0,0,0,360,3.1,1,1,
18 2015,1,1,10,60,?9?9?9?9E0?9?9?9?9?9?9?9?9?9?9?9?9*9*9*9*9*9,-17.8,-22.2,66,98607,163,1325,184,23,105,16,2747,0,191
19 2015,1,1,11,60,?9?9?9?9E0?9?9?9?9?9?9?9?9?9?9?9?9*9*9*9*9*9,-17.5,-22.0,65,98708,298,1415,175,157,658,41,18373,161
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Figure 4: 'epw' file sample, showing header from lines 1 to 8 and weather data from line 9.

The outputs are the result of simulating the model using the above input files, and users are able to generate a variety of outputs based on their needs.

Various studies intended to use EnergyPlus to pre-evaluate building envelope designs to identify the most energy-efficient option. For example, in a study by Bojić et al. (2014), the impact of using a Trombe wall on the south side of a house in Lyon, France, was investigated to understand the amount of total energy saving. Another study used EnergyPlus for validation and verification of Phase Change Materials (PCM) for opaque wall assemblies and investigation of variables that affect their thermal performance (e.g., PCM properties and location in building envelope). A similar approach is implemented as dictated by the American Society of Heating, Refrigeration and Air Conditioning Standard 140, consisting of analytical verification, comparative testing, and empirical validation (Tabares-Velasco et al., 2012). Also, by integrating the experimental results from the materials and components into the EnergyPlus simulation tool, researchers and designers can quantify the amount of energy savings. Silva et al. (2016) quantified vegetated roofs' energy savings in the Mediterranean climate with distinct heating and cooling seasons using an experimental result to calibrate building energy simulation in EnergyPlus. In another experiment using the EnergyPlus, Wei et al. (2010) implemented the network model of a dual airflow window into EnergyPlus to analyze the energy performance of 60 m² apartments installed with the dual airflow windows in five different climate zones in China.

Moreover, various researchers have investigated the behavior of the users of buildings since the operational and space usage characteristics of building occupants are integrally linked to energy consumption (Hoes et al., 2009). Chen et al. (2017) used co-simulation with EnergyPlus to model occupant behavior and analyze its impact on the energy consumption of a small office building in Miami, FL, using an occupant behavior functional mock-up unit (obFMU). However, some studies pointed out the limitations of EnergyPlus for fully modeling the energy performance of the buildings. For instance, Ramos & Ghisi, (2010) compare EnergyPlus and Radiance, evaluating the useful daylight illuminance (UDI) and daylight factors (DF) index for three different types of rooms. The research highlights an EnergyPlus limitation related to light decay calculations in deep rooms. Mun et al. (2020) analyzed semi-transparent photovoltaic (STPV) modules simulated in the EnergyPlus and compared them to mock-up data. The results showed that the simulation did not reflect a temperature increase of modules during power generation and the indoor temperature increase by the radiation.

2.3 Weather data

The building industry primarily uses weather data to investigate the building's design soultions and energy performance during the design and planning phase. Reliable weather data is becoming more crucial as we experience more extreme events because of climate change (Herrera et al., 2016). Short-interval climatic data are one of the most critical inputs for building simulation models. These data specify the boundary conditions for the component models used in simulation applications. Environmental data should preferably be collected on-site, considering all local conditions.

Furthermore, the observations should be made at intervals consistent with the modeling being done. The development of observation processes mainly focused on general forecasting, aviation, and agriculture, but requirements for engineering applications were given little thought. As a result, building simulation is frequently forced to use the available data. Recent advances in technology resulted in cost reduction and increased complexity of data, improving the amount of data available for modelers and researchers (Hensen & Lamberts, 2012).

While many weather stations exist throughout the world, most do not record all the data required for the buildings' energy simulation. They often exclude solar radiation from the observations. Also, limitations and uncertainties in recording, observing, and reporting the weather data often impact their reliability and suitability for energy simulations. In this respect, Brönnimann (2015) outlined the uncertainties which can affect the reliability of the weather data parameters, such as measurement uncertainties (Instrument calibration, malfunction), procedural uncertainty(errors in reporting), Representativeness in time and space (Station relocation, change in observation times), and uncertainties related to post-processing the data. Table 1 summarizes the main environmental parameters for making the simulation of buildings feasible.

Table 1: Required environmental parameters for energy simulation.

Dry bulb air temperature (°C)
Wet-bulb temperature (°C)
Wind speed (m/s)
Wind direction (° from the north)
Atmosphere pressure (bar)
Net longwave radiation (W/m²)
Precipitation (mm)
Global horizontal (direct normal) solar radiation (W/m²)
Diffuse horizontal solar radiation (W/m²)
And, where solar radiation is not available:
Cloud cover and type (%,-)
Sunshine hours

From the weather parameters in Table 1, dry-bulb air temperature and wind speed are subjected to significant modifications as these parameters can be highly affected by local surroundings (microclimate). As a result, the weather station observations, usually located on open sites such as airports, can not accurately represent conditions, not in their vicinity (Hensen & Lamberts, 2012). solar and illuminance data are also critical values for building simulations, and they are usually generated using models (Davies & McKay, 1989; Myers et al., 2005).

Historically weather parameters for simulation of the buildings have been represented in a file consisting of 8760 hourly values of a year since one-hour intervals are used in most building simulations. The form of full-year hourly data was developed for two main reasons; traditionally, most weather records were manually conducted, and hourly measurements were practical for most applications. Moreover, hourly weather data has been used in most BPS tools as a regular interval since it is short enough to collect behavioral responses but long enough to allow for practical implementation (Hensen & Lamberts, 2019). However, some studies suggest that sub-hourly time steps are also necessary to evaluate the sophisticated interactions (D. B. Crawley et al., 1999). For instance, a study by Janak (1997) showed about a 40% difference in the prediction between hourly and 5-minute interval solar data.

Building performance simulation, especially in large commercial buildings, requires performing detailed heat balance calculations hourly over a year. Furthermore, simulations using weather data measured from multiple years are time-consuming, demand computational power, and are less skillful (T. T. Chow et al., 2006). Also, performing with weather data of a specific year may cause inaccuracies depending on the selected year (Üner & İleri, 2000). The Typical Weather Year (TWY) is the most common weather data used in building energy simulation tools. TWYs have gained widespread acceptance in the building simulation community because they represent average climate patterns related to a building's thermal behavior in average conditions. The need for typical and localized weather data was first recognized in the 1970s when numerical methods for building performance simulation emerged—in the UK, Example Year, developed by Holmes & ER, (1978), was an attempt to represent a single year from statistical analysis of the hourly observation from 1956 to 1975. The selection procedure of Example Weather Year involves the nomination of the year that contains the minor irregularities. In the US, the Test Reference Year (TRY) in the 1970s was one of the earliest attempts to select one year from a multi-year dataset that effectively represents the selected period (NCDC, 1976). This procedure for TRY , introduced by National Climate Data Centre (NCDC), was developed for 60 US locations using a procedure in which years in the observed period between 1948 and 1975 that had months with extremely high or low mean temperatures were gradually omitted until only one year remained. TRY weather datasets include climatic parameters, such as dry bulb temperature, wet bulb temperature, dew point, wind direction and speed, barometric pressure, relative humidity, cloud cover, and type, but they lack solar radiation data. There has not been a widely accepted methodology for TRY selection (T. T. Chow et al., 2006), and researchers in different countries adopt different criteria for the selection (Clarke, 2001; Festa & Ratto, 1993; Lee et al., 2010; Miguel & Bilbao, 2005). TRY lacked solar data and extreme events and led to the development of an approach called Typical Meteorological Year (TMY). National Climate Data Centre (NCDC) is associated with the Sandia National Laboratory for 234 US locations (Typical meteorologicalyear u ser's, 1981). A TMY consists of twelve Typical Meteorological Months (TMMs) chosen from a multi-year weather database and selected from various calendar months (I. J. Hall et al., 1979). Each month is arranged from different years with the condition that it has to represent the statistical characteristic of the climatic conditions of that month. Unlike the TRY datasets, TMY consisted of solar radiation data.

Even though only 26 locations had measured solar data, the remaining 208 sites had to rely on parameters of the cloud (T. T. Chow et al., 2006). Various procedures have been developed to generate TMY. (I. J. Hall et al., 1979) developed a process for selecting TMMs using Finkelstein–Schafer (FS) statistics. (Bulut, 2004; Chan et al., 2006; Pissimanis et al., 1988; Zhou et al., 2006) used the same method to generate TMY for varying locations. (Lund & Eidorff, 1981) developed a process for generating TMY named the Danish method, by converting climatic parameters into residuals, then analyzing the residuals to create statistical indicators to select typical meteorological months that are elements of TMY to eliminate the effects of seasonal change. (Andersen et al., 1977) also use a similar approach as the Danish method for constructing the TMY months. Some other researchers (Feuermann et al., 1985; Petrie & McClintock, 1978) used different procedures for constructing TMY only for solar radiation. (Festa & Ratto, 1993) used a more complex approach for constructing TMY. They compared the frequency distribution relative to every month in the database with the long-term frequency distribution of the months with the same name. (Bilbao et al., 2004) conducted a comparative study using three methods of TMY methods (the Danish, Argiriou, and Pissimanis) for two sites in spain. The results showed that the effectiveness of the various TMY methods is influenced by the measurement station's location as well as the solar energy system studies. Among the proposed method of TMYs, the method developed in 1978 by Hall et al. has become more common in the building simulation community.

ASHRAE commissioned research projects from 1970 to 1983 to create a weather data set that would represent more typical weather patterns than either a single representative year or a collection of months. Weather Year for Energy Calculations (WYEC) weather dataset was constructed from 30 years of records (ASHRAE, 1985). The basic strategy was to spot possible calendar months with real-time hourly data that could fill the year's twelve vacancies.

The original WYEC and TMY files were then updated by the National Renewable Energy Laboratory (NREL) and ASHRAE in the early 1990s. Weather Year for Energy Calculations 2 (WYEC2) is an extended version of the WYEC data format consisting of calculated hourly illuminance and zenith luminance data for easing daylighting applications (ASHRAE, 1997). NREL also developed the TMY data set's second version, TMY2, with a new period of records from 1961 to 1990 for 239 locations in the US (Marion & Urban, 1995). TMY2 is comparable to TMY but with more complicated solar models. Also, weightings give more emphasis to dry bulb and dew point temperatures and less to wind speed. The NREL also created a more recent version of TMY with a similar method to TMY2 based on 15 basis years from 1991 to 2005 (Wilcox & Marion, 2008a, p. 3).

In the mid-90s, ASHRAE acquired the weather data of 900 international locations outside the US and Canada from NCDC. The International Weather for Energy Calculations (IWEC) weather files were developed under one of the ASHRAE's research projects and attempted to unify the weather files (Thevenard & Brunger, 2002, p. 1). IWEC has been updated to IWEC2 weather files, which have lower weights for global horizontal radiation but higher weights for direct normal solar radiation than the IWEC (Joe et al., 2014).

National Research Council (NRC) and 2.5. Canadian Weather for Energy Calculations (CWEC)

Environment and Climate Change Canada (formerly Environment Canada) developed a procedure similar to the TMY based on the Sandia method to generate typical weather datasets for Canadian locations (Morris, 2016). The TMMs are selected from the historical weather data from the Canadian Weather Energy and Engineering Datasets (CWEEDs). The main difference between

CWEC and TMY is that CWEC files are organized in the WYEC (Morris, 2016). Also, more recent historical weather data from CWEEDs are stored in WYEC3 (.WY3) format, which needs to be converted to EPW format in order to be used by BPS tools. Few studies (Siu et al., 2019; Siu & Liao, 2020a) developed methods to convert the WY3 files into a format that can be used for BPS tools.

Most of the typical weather years introduced above were based on constructing a full year of hourly data based on months with average weather conditions; thus, and are appropriate for simulation of typical building operation. Using average weather conditions in generating TWYs does not provide any information related to the weather fluctuations, extreme events, or atypical climatic conditions. Extreme events, such as cold snaps, drought periods, and heat waves, are critical for modeling peak heating and cooling loads in buildings (M. J. Holmes & Hacker, 2007), evaluating the thermal comfort of occupants (Yang et al., 2014), and overheating (Jentsch et al., 2014). As a result of climate change and increasing occurrences of extreme events in weather conditions (Coley et al., 2012; Herrera et al., 2016), BPS and Building Engineering communities are integrating these changes into the building design and their impact on occupants' behavior. Some researchers attempted to modify the current TWYs for evaluating buildings under these extreme conditions. For instance, (Pernigotto, Prada, Gasparella, et al., 2014) modified the weighting of the different weather parameters for constructing the TRY based on the intention of the weather data for evaluating the cooling or the heating. Also, some methods have been developed specifically to represent the atypical years. Chartered Institution of Building Services Engineers (CIBSE) Design Summer Year (DSY) attempts to assess overheating and predict the impact of warmer than average summers for estimating the sizing of mechanical cooling systems (Virk et al., 2015). The Extreme Meteorological Year (XMY) procedure is similar to the TMY procedure for using the same weather variables and weightings (D. B. Crawley & Lawrie, 2015). However, in the XMY procedure, the selections are based on extremes instead of average conditions from the selected period. Another approach is WYEC2 reference years calculated with different than standard weighting indices known as Untypical Meteorological Years (UMY) (Narowski et al., 2013). The UMY procedure assigned more weights to the maximum and minimum dry bulb temperatures, solar radiation, and wind speed parameters. Although the weather datasets for extreme conditions are helpful for evaluating the buildings' peak energy uses, according to the studies (Georgiou et al., 2013; Narowski et al., 2013; Pernigotto, Prada, Gasparella, et al., 2014), the TMYs are satisfactory enough to reflect typical building operations.

It is not easy to establish a single procedure that consistently outperforms the others regarding different selection procedures. Some studies show that energy simulations using different typical weather years have similarities (Chan, 2016; Janjai & Deeyai, 2009), while other studies showed discrepancies in annual energy consumption (Bhandari et al., 2012b; Skeiker, 2007; Sorrentino et al., 2012). The discrepancy between the actual energy demand and what is predicted may impact the decision-making process during the design phase. Also, various studies suggested that a single typical weather year can not accurately represent the year-by-year variation in the energy demands of the buildings. Although the TWYs simplify the procedure for building performance predictions and reduce the amount of work, time, cost, and computational power, Some flaws stem from the chosen method for obtaining weather data. Whichever approach is used for generating TWYs, the weather variables and weightings for a typical year are calculated according to the same criteria. However, the criteria for generating a typical year rely on the building system type. For instance, for building systems heavily dependent on solar radiation, one should assign more weight to the solar radiation data to develop a typical weather year, and for the buildings that use natural ventilation, the wind speed is more important. Another study compared the result of the simulation for different systems using 17 TRY. The results demonstrated that the most optimal TRY varies from system to system (Argiriou et al., 1999). (Dean & ASA, 2010) finds that PVWatts solar PV production tool using TMY2 weather data overestimates the monthly production by 6% over the average and more than 90% of the predicted production using historical data.

Moreover, the TWY dataset does not always reflect the average value of the long-term historical weather data, and the fluctuations and atypical occurrences are usually neglected. Some authors concluded that TWYs adequately reflect the long-term average of actual years (W. K. Chow & Fong, 1997; Kershaw et al., 2010; Yang et al., 2008). another study, however, resulted in high variation between the average of typical; weather years and historical data in some locations (Pernigotto, Prada, Cóstola, et al., 2014).

Additionally, different procedures for generating typical weather years result in different outcomes. For example, in a study by (Skeiker, 2007), six methods for generating TMY were obtained for ten years of hourly measurements to predict thermal system performance in buildings. The results showed that each method had diverging outcomes, with the Sandia method being the closest to the average performance of the building's thermal system. A study also simulated annual energy consumption for three types of buildings using varying typical weather datasets. The comparison showed that annual building energy consumption varies by ±7%. Also, monthly building loads can vary by ±40% depending on the provided weather data location.

A single-year weather dataset can not sufficiently reflect the fluctuations in actual weather data. Using typical years, the variation between the buildings' predicted and actual energy demands is more noticeable for uninsulated lightweight residential buildings in the heating season (Argiriou et al., 1999; Pernigotto, Prada, Cóstola, et al., 2014). This variation is less evident in the cooling season than in the heating season unless for the high window to wall ratio buildings (Pernigotto, Prada, Cóstola, et al., 2014). Also, a study by Hosseini et al. (2017) suggests that the roofs with the highest insulation levels have the least overestimated space conditioning energy needs. The study concluded that most cool roof designs estimated by CWEC tend to be overestimated in space conditioning.

Furthermore, the climate is a complex and variable phenomenon. Historic Datasets should also reflect current climate conditions and rely on more recent weather observations. Some authors suggest that the use of outdated typical years causes overestimation in significant demand for space heating while underestimating demand for space cooling (Kočí et al., 2019b; Siu & Liao, 2020b).

With recent developments in computational power, currently, it is possible to run hundreds of simulations in less than an hour. Considering the limitations and flaws in using the typical weather datasets, one should also consider the simulation using the Actual Weather Years (AWY). Rather than providing a single value, such assessments using multi-year weather datasets provide a range of building energy use due to the changing climate. It allows the policymakers and designers to estimate the probability of any weather condition and establish proper approaches based on the simulation results.

2.4 Summary

Designing sustainable and energy-efficient building requires considering possible mechanisms like climate change, the depletion of non-renewable energy sources, growing needs and expectations for occupants' thermal comfort, and increased awareness of the connection between the indoor environment and occupants' well-being. Building performance simulation is now a crucial part of the design process for new construction and assures adherence to energy regulations. The BPS is also a valuable tool for optimizing the energy performance of the existing buildings. However, one of the most frequently discussed topics about building energy simulation tools is the energy performance gap, which is the mismatch between the actual and predicted energy demand.

BPS tools need hourly weather data for predicting buildings' energy performance. The most significant influence on a building's energy efficiency comes from the climate, particularly today when global weather patterns are constantly changing. Weather data are one of the sources of uncertainties that can cause the energy performance gap in buildings; hence, designers and researchers should be aware in selecting the most appropriate weather data for energy simulations. The most common form of weather data for building simulations is Typical Weather Year (TWY), which contains 8760 hourly values of meteorological parameters derived from a long-term database through statistical processing in a one-year sequence. Typical weather years simplify the simulation process, reduce the computational time, and are reasonably accurate. However, TWYs cannot represent the present-day climatic conditions and year-by-year fluctuations in weather parameters. With increased computational capacity, it is now feasible to use the actual year-by-year weather data in the energy simulations.

Therefore, more research is required to identify the impact of different typical weather and actual weather dataset on the energy predictions of the BPS tools under different climates and building typologies.

3 Impact of typical-year and multi-year weather data on the energy performance of the residential building using controls appropriate for Canadian weather conditions

Abstract

Climate has the highest impact on the energy performance of the buildings. Therefore, it is crucial to use reliable weather data to evaluate the energy demands of the building and reduce the performance gap. Typical weather years (TWYs) have been used for the energy buildings simulation for a long time despite existing flaws. A single-family house in Winnipeg, Canada, is selected to investigate how TWYs affect energy consumption and compare them with multi-year simulations. The investigation findings revealed that a typical year could not capture the whole spectrum of year-by-year weather variations. Hence the results show that the two typical weather years (CWEC and TMY) overestimated the cooling load while underestimating the heating load compared to the last five actual weather years. Today with increased computational capacity, it is possible to use actual weather years for multi-year simulations of the buildings to improve the assessment of their energy performance.

3.1 Introduction

The building sector is accountable for around 35% of final energy consumption and approximately 39% of energy-related carbon dioxide emissions (IEA, 2019). To address this issue, code requirements for the energy performance of buildings are becoming more stringent worldwide. Building scientists and designers must investigate different design strategies and novel and advanced materials and technologies to satisfy these high standards. Dynamic building energy simulation is a robust technique that provides a pathway to test, analyze, and optimize energy efficiency measures and technologies (Al-janabi et al., 2019; Dutta & Samanta, 2018; Korolija et al., 2013; Mousa et al., 2017). However, since building energy modeling became an integral part of the building design process and compliance with energy codes and regulations, one of the most discussed issues in the design community is the energy performance gap. In this respect, several studies showed that selecting the weather file for the simulation significantly impacts the modeling predictions (Huang & Crawley, 1997). As a result, choosing appropriate weather files is critical for precise and accurate model predictions.

One of the widely used forms of weather data is typical weather year (TWY), a full-year hourly weather data derived from a long-term database through statistical processing. There are several approaches for creating TWY files, such as Typical reference year (TRY) and Typical Meteorological Year (TMY), and others with different precisions in predicting the energy performance of the building (Lee et al., 2010).

TWY has made the prediction process easy, and it is reasonably accurate in evaluating the energy performance of the building in the long term. Also, the TWY approach reduces the amount of effort and time for the energy simulations. However, there are several critical issues related to the use of TWY (Chan et al., 2006). Typical Weather Year cannot reflect the year-by-year fluctuations in the weather condition in a single year, and they usually discard the extreme conditions. And as a result, they are not appropriate for estimating peak loads for sizing the heating, cooling, and ventilation equipment. In addition, TWYs are created using different procedures and methods, and consequently, they may produce different results.

Also, TWY files are often outdated and are not generated from recent weather data. In this respect, TWY built upon historical data might not represent the present-day climate conditions, especially considering climate change. Because Canada is heating up at approximately twice the global average, weather files should rely on recent observations to provide reliable predictions about the energy performance of the buildings (Kočí et al., 2019; Siu & Liao, 2020). For example, in a study by Yang et al. (2008), authors compared older typical weather data in Toronto city with a more recent weather file. The study shows 6-36% overestimation in heating load and 12-31% underestimation in cooling load. These results suggest significant uncertainty related to using outdated weather data.

Nowadays, with increased computational capacity, it is possible to run multiple simulations using Actual Weather Years. Evaluating multi-year actual weather data allow researchers and designers to understand the performance of the building in a long period and changing climate reflected in each year (Siu & Liao, 2020).

A few studies currently investigated the advantages of using Actual Weather Years (AWY) compared to running the simulations with Typical Weather Years (TWY). One of the first studies was conducted by Crawley (1998), who investigated the influence of various weather data sets on annual energy consumption, peak loads, and cooling and heating demand in eight different office spaces in the U.S. The study then compared the results with 30 actual weather data showing that energy consumption varies between -11% to 7% in the 30-year actual weather data set compared to the multi-year weather dataset. Evola et al. (2021) used multi-year and typical-year approaches to investigate the energy use of an office building and a residential building in Sicily, Italy. According to the authors, TWY resulted in 10-35% and 15-25% underestimation in choosing the correct heating and cooling systems size.

This study aims to extend the current understandings in applying different weather datasets for energy simulations and compare the impact of these datasets on the energy performance of the building exposed to extreme cold climate. It compares the energy performance of a single-family house located in Winnipeg, Canada, by applying multi-year and typical year weather datasets from a weather station. Hence two TWY files typically used by the building energy modelers and five actual weather years recorded from 2015 to 2019 were investigated and compared.

3.2 Methods

3.2.1 Weather data selection

Two most recent TWYs procedures were selected for the research, including Canadian Weather year for Energy Calculation (CWEC), covering the 1998 to 2017 period derived from the Canadian Weather Energy and Engineering Data Sets (CWEED), and TMYx(15), including the 2004-2018 timeframe available from the online repository climate.onebuilding.org. CWEC was developed by Environment and Climate Change Canada (previously Environment Canada) and the National Research Council as a Typical Year weather dataset for Canadian Locations. CWEC, like TMY, is a weather dataset created based on the Sandia selection method (I. J. Hall et al., 1979). The representative meteorological months are selected from the Canadian Weather Energy and Engineering Datasets (CWEEDs). TMYx files are typical meteorological data derived from hourly weather data in the ISD (US NOAA's Integrated Surface Database) using the TMY/ISO 15927-

4:2005 methodologies. The authors of climate.onebuilding.org created TMYx datasets. The primary distinction between CWEC and TMY is that CWEC files are structured in the ASHRAE-developed WYEC (Weather Year for Energy Calculations) format (Siu & Liao, 2020). The selected months for constructing both typical weather years are shown in Table 2.

Table 2: Period selection of typical weather years based on different procedures.

Typical Weather Year	Period	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
TMY	2004-2018	2015	2009	2017	2017	2017	2011	2017	2015	2006	2008	2006	2018
CWEC	1998-2017	2002	2009	2017	2011	2012	2011	2010	2015	2017	2008	2006	2009

The nearest weather station with the requisite data for producing typical and actual weather files is the Forks weather station, located approximately 9 km from the case study near the junction of the Red and Assiniboine rivers in Winnipeg, as shown in Figure 1. Due to the dramatic changes in Canada's climate over recent years (Siu & Liao, 2020b), we used current actual weather data. Therefore, hourly weather data was collected from the Forks weather station from 2015 to 2019. Obtained weather data contains hourly values for a variety of environmental parameters such as dry bulb temperature (°C), wind speed (m/s), relative humidity (%), wind direction, and atmospheric pressure (hPa). The obtained hourly data contain all the required parameters for energy modeling except for solar radiation. As a result, solar radiation data were obtained from NSRDB (National Solar Radiation Database) nsrdb.nrel.gov.

EnergyPlus weather file (.epw) is one of the most widely used formats that can be read by building performance simulation (BPS) tools and is compatible with various energy simulation programs. Hence, the AWYs and TWYs of both climates were organized into the (.epw) format to be used in the BPS tool.

3.2.2 Building description and modeling

The two-story single-family house with a total floor area of 185 m² (136.33 m² conditioned) in Winnipeg, Manitoba (see Figures.5 B and 6) was used to investigate the impact of multi-year and typical year weather datasets on its energy performance.

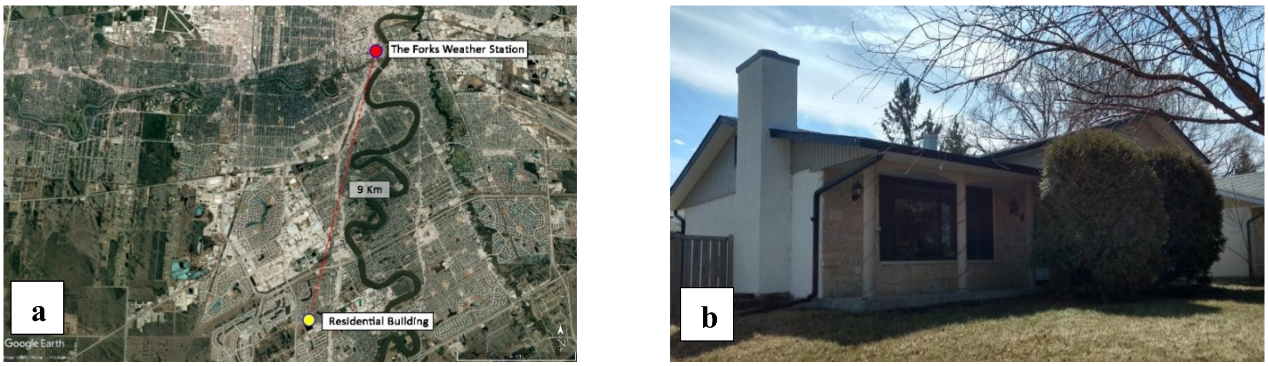
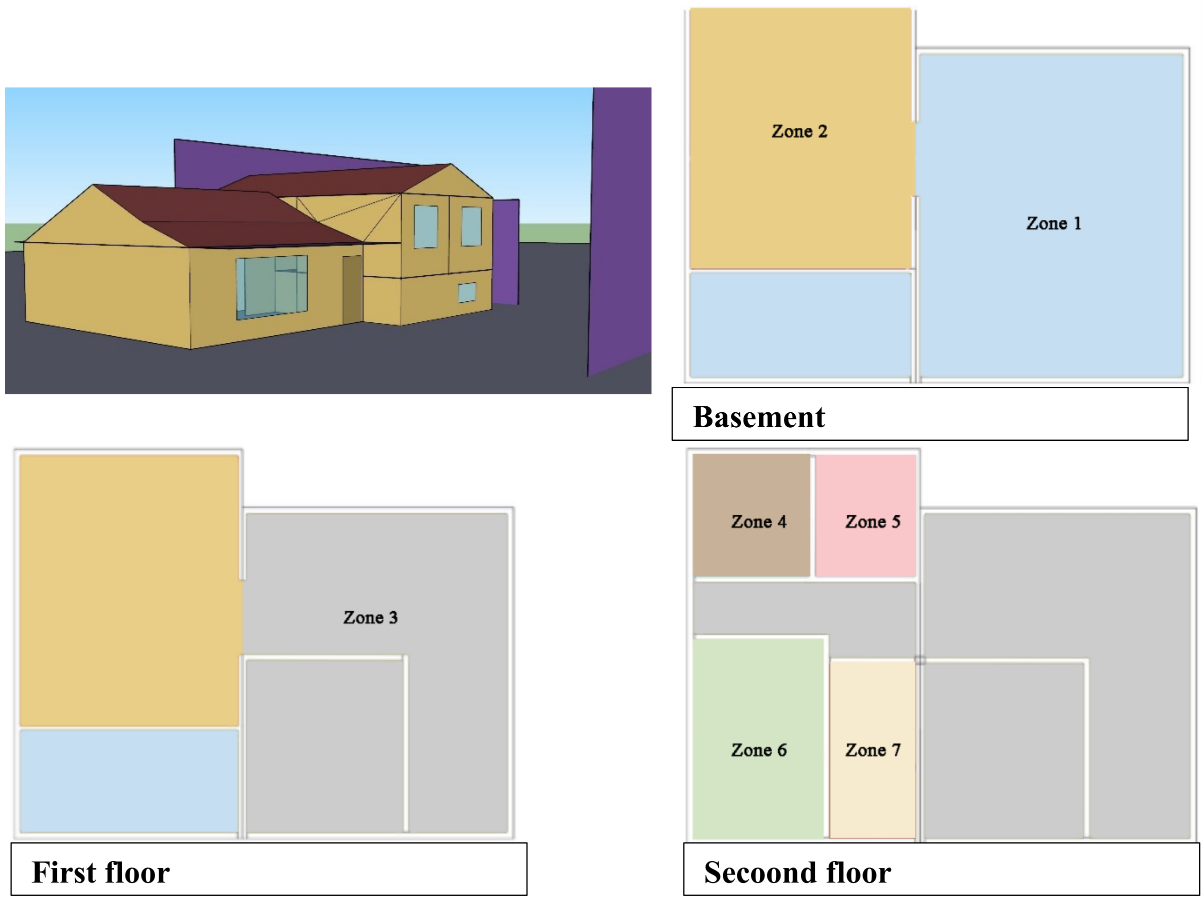


Figure 5: The location of two weather stations (A) and the actual house (B)

The house built in the 1970s has the orientation of 27° west to the true north. Its layout includes three bedrooms, a kitchen and living room on the ground floor, two bathrooms, an insulated crawl space, a utility room, and ventilated open space at the basement level. Therefore, we defined nine thermal zones presented in Figure 6.



Zone1 Basement	**Zone4** Bedroom	**Zone7** Bathroom
Zone2 Utility room	**Zone5** Bedroom	**Zone8** Roof attic
Zone3 Kitchen, Hallway,Living room	**Zone6** Master bedroom	**Zone9** Roof attic

Figure 6: modeled building and the thermal zones

The east and west exterior walls of the house do not have windows. The exterior north and south-facing facades have 15% and 20% window-to-wall ratios. The framing system is conventional and is constructed with two by four wooden studs spaced at 16 inches and insulated with fiberglass batt. Double pane clear glass filled with air is used for glazing systems. The concrete basement slab is 225 mm thick. Moreover, 19 mm of wood subfloor, 12.7 mm of sheathing, and two layers of plywood (16 mm+12 mm) made up the floors. In the case of the roof, the plywood (16mm) and roof sheathing (13mm) are separated by ceiling air space resistance, while the asphalt shingles form the outer layer. Table 3 summarizes the envelope components' thermal transmittance values (U-values).

Table 3: U-values of envelope components

	Building Components					
	Basement Slab	**External Walls**	**Floors**	**Windows**	**Roof**	**Interior walls**
U-Values [W/m2-K]	1.674	0.288	1.568	2.4	0.14	1.71

The first energy model for the single-family house was developed in energy plus, using the existing heating and cooling system and validated against the actual measured data. In this study, the heating and cooling loads in the building are estimated using an ideal load air system scenario. The ideal load air system is an object in EnergyPlus intended to deliver heating and cooling to a zone with 100 percent effectiveness to meet any heating or cooling requirement of the zone. This scenario allows the evaluation of the building's geometry and envelope performance without modeling heating and cooling systems (*EnergyPlus input-output*, 2021). The heating setpoint of 20 °C and cooling setpoint of 23 °C were used in the EnergyPlus model.

3.3 Results and discussion

3.3.1 Weather data

This section investigates the meteorological data recorded by the Forks weather station from 2015 to 2019 and compares it to the statistical distribution of typical weather years (TWY), CWEC, and TMY. In this respect, Table 4 summarizes their annual minimum, mean, and maximum outdoor air dry bulb temperature, relative humidity, wind speed, and global horizontal irradiance. The yearly variation between the environmental parameters, except wind speed, is not considerable between the TWY and five actual weather years (AWY). Thus, CWEC and TMY have a significantly lower annual mean wind speed of 2.1 and 2.08 m/s, respectively, than five AWYs with wind speeds ranging from 6.54 to 7.79 m/s.

Table 4: Annual Minimum, mean, and maximum values of four environmental parameters

	Dry-bulb air temperature			**Relative humidity**			**Wind speed**			**Global horizontal irradiance**		
	Min	**Mean**	**Max**	**Min**	**Mean**	**Max**	**Min**	**Mean**	**Max**	**Min**	**Mean**	**Max**
Unit		°C			%			m/s			Wh/m²	
2015	-29.48	5.67	33.30	13.00	67.28	97.00	0.00	7.79	42.50	225	3730	8643
2016	-27.80	6.13	34.31	10.38	68.83	97.63	0.00	6.68	22.50	201	3683	8842
2017	-31.10	4.93	33.48	13.00	65.47	97.00	0.00	6.85	25.00	116	3706	8643
2018	-28.30	4.19	36.40	11.00	64.68	96.00	0.00	6.54	25.00	273	3667	8542
2019	-34.65	3.43	35.28	15.63	66.05	99.00	0.00	6.92	25.00	309	3702	8870
CWEC	-28.45	4.66	33.30	12.38	68.40	99.00	0.00	2.10	9.36	291	3575	8456
TMY	-28.96	4.94	33.30	13.00	66.14	100.00	0.00	2.08	11.68	206	3657	8519

Additionally, Figure 7 illustrates the distribution of dry-bulb air temperature and global horizontal irradiance in January and July. Boxplots present the results, and for conciseness, we selected the coldest month (January) and the warmest (July) for the comparison. Boxplots include a vertical box from the first quartile to the third quartile, and a horizontal line inside the box represents the median. The whiskers go from each quartile to the min and maximum of the data. Also, the green dots in the boxes demonstrate the mean of each data distribution. The length of the whiskers is limited to 1.5 times the interquartile range by varying the box and whisker plot. Thus, the whisker reaches the value farthest from the center while remaining within 1.5 times the interquartile range from the lower or higher quartile. Outliers shown as red crosses on the graph are data points that fall outside this range. Figure 7 shows a declining trend in both median and mean values of the air dry-bulb temperature in January of the last four AWY. The results also indicate that the variation range of actual weather years is between 30.96 °C and 39.15 °C in January. The temperature difference between maximum and minimum of 34.72 °C for CWEC and 33.28 °C for TMY is comparable to 2015 (33.42 °C) and 2017 (33.23 °C). The coldest January was in 2019, with the highest temperature difference from -34.65 °C to 4.50 °C. In contrast, 2016 January was the warmest with the lowest variation in temperature between -26.50 °C and 4.46 °C. Furthermore, 2016 January appears more skewed negatively, while 2015 January is more skewed positively than the rest of the years.

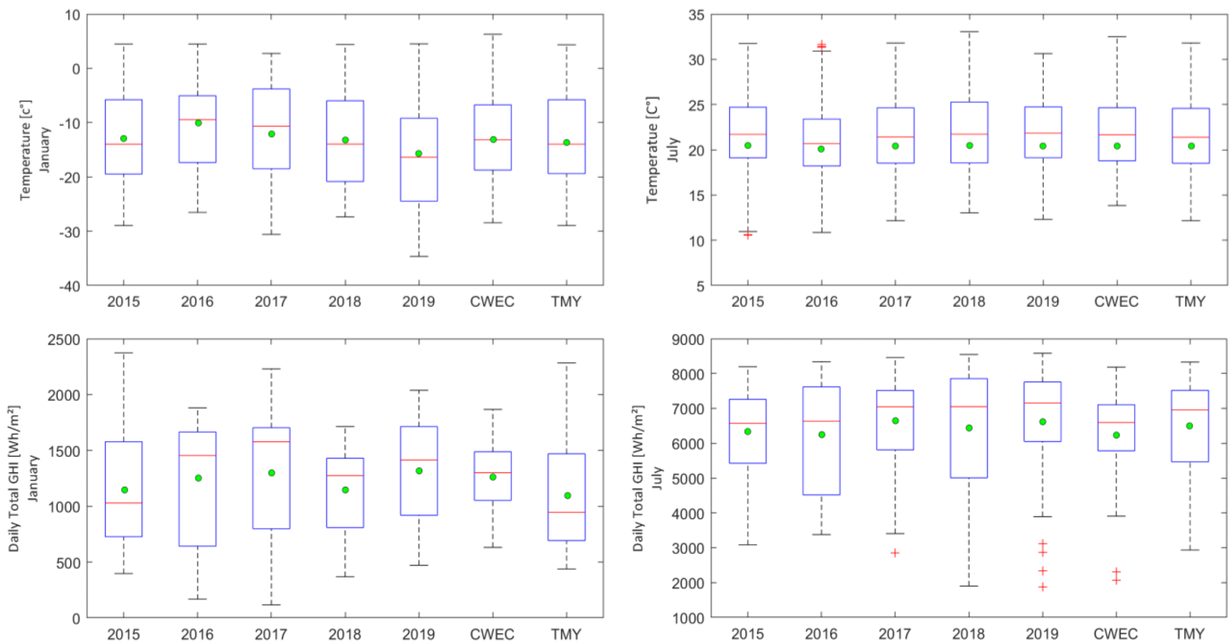
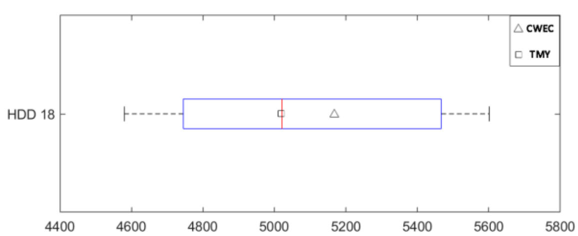


Figure 7: Distribution of the dry-bulb air temperature and global horizontal irradiance in January and July

In the case of global horizontal irradiance (GHI), the average variation over the five years ranges between 1125 Wh/m² to 1375 Wh/m² in January and 6226 Wh/m² to 6575 Wh/m² in July. There is a significant variation in GHI between two typical weather years. In this respect, the distribution of January and July GHI of CWEC is considerably lower than TMY. January 2016 had the most extensive distribution of GHI, followed by 2017. Also, 2016 and 2017 are negatively skewed, similar to 2018, whereas the 2015 and TMY distributions are skewed positively. July 2016 also had the most extensive distribution of GHI, followed by 2018. Global horizontal irradiances in July 2017, 2019, CWEC, and TMY appear skewed negatively.

3.3.2 Heating degree days and cooling degree days

Figure 8 presents the annual heating degree days based on 18 °C (HDD18) and cooling degree days based on 23 °C (CDD23) to provide a detailed look at the variation in real weather data for recording years from 2015 to 2019. Considering the HDD, the TMY weather data is very close to the median of the five-year actual weather data, while the CWEC exceeds by 3% the median (HDD= 5172°C.day). Regarding the CDD, the TMY year aligns with the median of the five-year actual weather data, whereas the CWEC year surpasses by 19% the median of the actual weather years (CDD = 30°C.day). These findings suggest that TMY better describes the current weather conditions than CWEC weather data in dynamic simulation of the building for predicting the cooling and heating demand of the building. Nevertheless, conclusive conclusions require further analysis of heating and cooling energy simulation predictions.



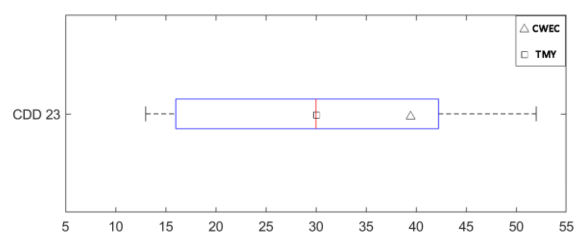


Figure 8: Heating and cooling degree days. Notes: the boxplots represent the multi-year distribution, and the shapes on the charts show the actual value for the typical weather year data.

3.3.3 Energy simulation of the residential building

This section seeks to investigate the impact of typical and actual weather years on the energy performance of the building. Figure 9 illustrates that the annual energy demand and peak energy demand computed using the actual weather year simulations fluctuate across a broad range, especially heating demand and peak. Thus, the heating demand distribution appears positively skewed, with the amplitude range between minimum and maximum values for heating demand being around 15 kWh/m². similarly, the distribution of cooling demand is skewed positively, ranging from 2.6 to 3.4 kWh/m².

The two typical weather years produce values close to one another and the median of the heating demand. However, the comparison of median values shows that TWY resulted in around 35% overestimated cooling load compared to the AWY.

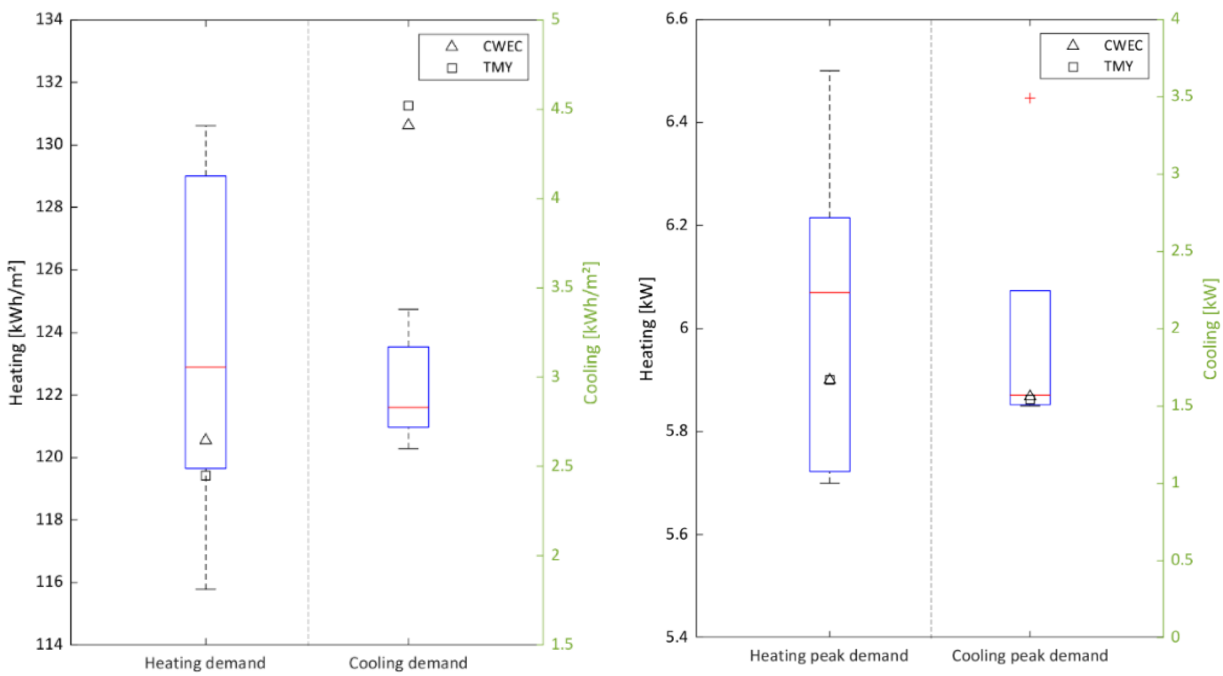


Figure 9: Heating and cooling loads and peak loads. Notes: the boxplots represent the multi-year distribution, and the shapes on the charts show the actual value for the typical weather year data.

The calculated heating demands using TWY fall in the interquartile range. Yet, there is a slight underestimation of approximately 2% when using TWY compared to the AWY. Figure 9 also shows that the two methods of typical weather years, CWEC and TMY, underestimate the heating peak loads by around 3 % of the median. Regarding the cooling peak load, CWEC and TMY weather data underestimate the peak loads by approximately -1%. Since mechanical systems must provide thermal comfort even in extreme weather conditions, these results suggest that using typical weather years might result in inappropriate heating and cooling equipment sizing. Figure 10 compares year-by-year fluctuations of the heating demand and the cooling demand, predicted by actual weather years' simulation against the predictions of two versions of typical weather years. Among actual weather years, 2019 has the highest demand for heating of approximately 130 kWh/m², closely followed by 2018 with 128 kWh/m². The weather years 2017 and 2015 have similar heating demand of around 120 kWh/m², while 2016 has the lowest of approximately 115 kWh/m². Typical weather years CWEC and TMY have similar heating energy consumptions of 120.6 kWh/m² and 119.4 kWh/m², respectively. Figure 10 also shows a considerable difference between cooling energy demand between two TWY and five AWY. Thus, the cooling needs of AWY range between 2.6 kWh/m² and 3.38 kWh/m², whereas they are 4.41 kWh/m² and 4.52 kWh/m² for CWEC and TMY, respectively.

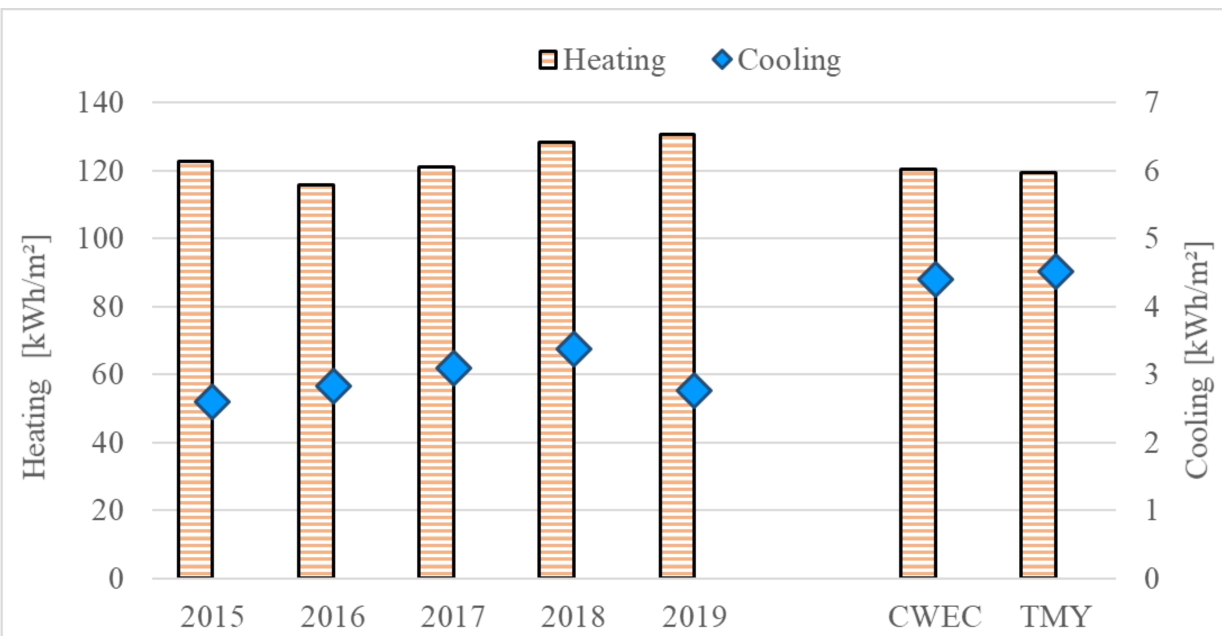


Figure 10: Year-by-year heating and cooling loads for five actual and two typical weather years

Furthermore, Figure 11 shows the year-by-year variation for heating and cooling demands based on the multi-year simulation approach, compared to single-year simulations. The percent variation is based on the average value of all AWYs from 2015 to 2019. Overall, the heating energy demand ranges from -6% in 2016 to 5% in 2019. The values calculated by the typical years approach were around 2% for CWEC and -3% for TMY. In contrast, cooling load shows a significant variation compared to the mean of multi-year simulation. Hence, CWEC and TMY overestimate the space cooling load by 50% and 54%, respectively. The likely explanation for differences in cooling energy demands between the weather years is a significantly higher wind speed (~70%) of five AWY than the two TWY (see Table 4). Similarly, because of the highest wind speed, 2015 has the lowest cooling demand among the five AWYs. Therefore, wind through the convection promotes heat dissipation from the house and reduces the cooling energy demand under AWYs compared to TWYs.

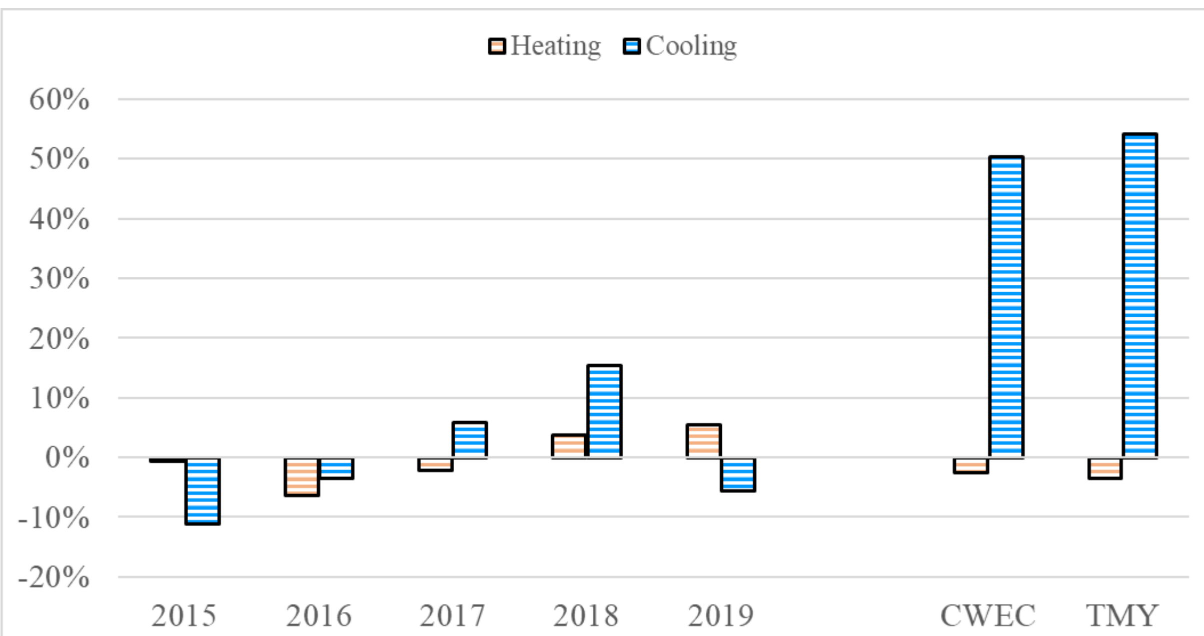


Figure 11: Year-by-year heating and cooling loads variation for five actual and two typical weather years.

However, to further investigate this assumption, we created two hypothetical typical weather files by replacing wind speeds in the CWEC and TMY files with the values from 2018. We selected 2018 due to its lower wind speed than other AWY (see Table 4). Figure 12 illustrates that an increase in the wind speed of hypothetical weather years resulted in an approximately 23%

reduction of their cooling energy demands compared to their counterparts and almost equated to the cooling energy demand of 2018. In contrast, as expected, the heating energy demand of the hypothetical years slightly increased (≈2%). The higher indoor-outdoor temperature difference during winter could explain the more pronounced impact of wind speed on cooling than heating energy demand during the winter months, which is the primary driver of heat transfer.

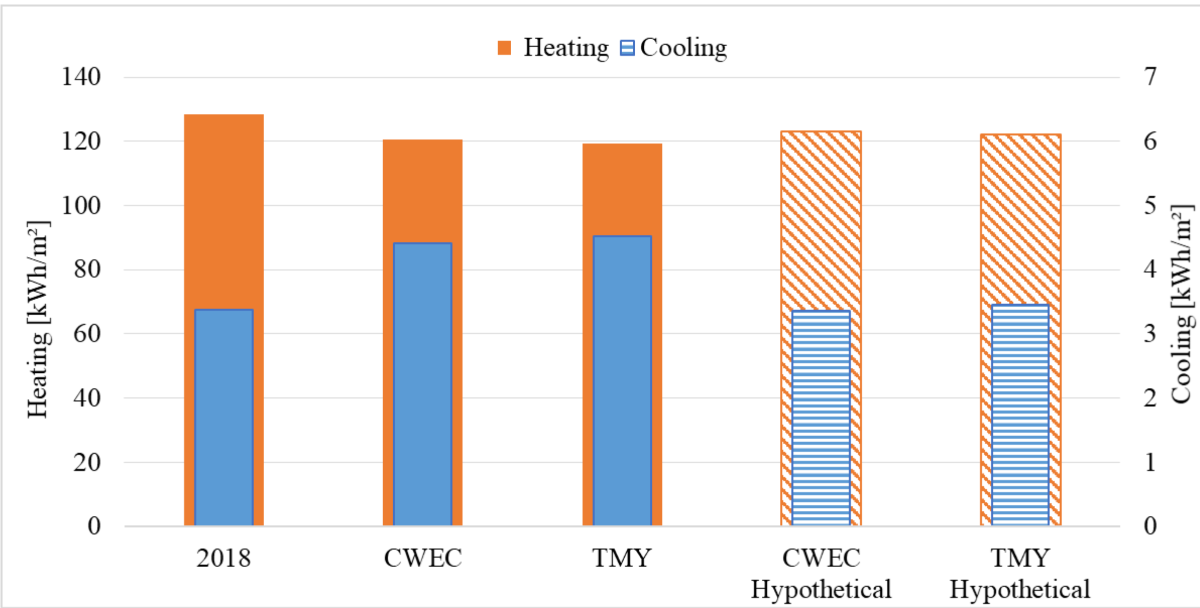


Figure 12: Year-by-year heating and cooling loads for 2018, two typical and two hypothetical weather years

4 Typical-year and multi-year weather data in building performance simulations: the role of climate and building typology on energy predictions

Abstract

Typical Weather Years (TWYs) have been used traditionally for Building Performance Simulations (BPS) to represent the average trend of long-term Actual Weather Years (AWYs) data through a single year. However, there is no evidence to determine if TWYs accurately reflect the changing climate. This paper aimed to compare the impact of TWYs with individual weather years from 2010 to 2019 on an example of a single-family house and a complex commercial building under cold (Winnipeg, Canada) and hot (Catania, Italy) climates. The analysis results revealed that weather data differed considerably from year to year over the ten actual weather years. TWYs of Catania (IWEC and TMY) underestimated the cooling loads of both buildings while underestimating the heating loads in most cases.

Furthermore, the TWYs in Winnipeg (CWEC and TMY) underestimated the heating demands, whereas they overestimated the cooling demands of both buildings. Hence, typical weather years cannot adequately consider annual variation in the buildings' energy demands. The findings from this study indicate that the use of multi-year simulation is necessary for a complete evaluation of the long-term energy performance of buildings, especially considering advances in computing capabilities.

4.1 Introduction

The building sector accounts for a significant share of global final energy consumption (35%) and energy-related CO2 emissions (39%). Building codes play a crucial role in setting standards for energy performance and are becoming increasingly stringent worldwide to reduce the long-term energy demand of the built environment (Golove & Eto, 1996; May & Koski, 2007; Probst, 2004; Vahidi et al., 2021). As a result, architects and engineers need to investigate various design solutions, including advanced technologies, to meet these high-performance requirements. Building performance simulation (BPS) is a very helpful and effective tool in this direction, and also allows testing, analysing, and optimizing energy-efficient measures for space heating and cooling (Al-janabi et al., 2019; Dutta & Samanta, 2018; Korolija et al., 2013; Mousa et al., 2017), while also enabling a rational decision-making process in compliance with energy codes (Hensen & Lamberts, 2012).

Whole-building energy simulation tools are essential in predicting building energy performance as they offer users key indicators such as energy consumption, carbon emissions, indoor environmental quality, and costs (D. B. Crawley et al., 2008). Over the past fifty years, building energy modeling developers have provided a broad range of BPS tools and have enhanced their reliability (*Best Directory | Building Energy Software Tools*, n.d.). Nevertheless, since building energy modelling became integrated into the building design and compliance processes with energy codes, the energy performance gap remains one of the most discussed concerns in the design community (Ahn et al., 2017; Gupta & Kotopouleas, 2018; Menezes et al., 2012a).

In this respect, several studies showed that the weather data used in the simulations are a significant source of uncertainties due to their significant effects on the model predictions (Cui et al., 2017; Evola et al., 2021; Hong et al., 2013; Hosseini et al., 2017; Yang et al., 2007). Available weather data are not always entirely reliable and representative of the actual weather conditions in a site because of the ongoing climate change, poor weather station maintenance, erroneous instrument reading, or inaccurate data digitization and post-processing (Brönnimann, 2015; *Technical Summary — Special Report on Climate Change and Land*, n.d.). Thus, choosing appropriate weather files is critical for reliable and accurate model predictions. The most commonly used form of weather data for building simulations is the Typical Weather Year (TWY), which contains 8760 hourly values of meteorological parameters derived from a long-term database through statistical processing in a one-year sequence. The American Society of Heating, Refrigerating, and Air-Conditioning Engineers (ASHRAE) first proposed this approach in the 1970s to examine building energy demand for air conditioning (Handbook, 2009). In this regard, ASHRAE compiled yearly weather datasets for several locations in the U.S. using a filtering procedure that discards years with extremely high or low air temperatures to develop the so-called Typical Reference Year (TRY). As a result, the TRY typifies an exceptionally mild year and does not sufficiently represent the long-term weather variability for a given site (Hui & Lok, 1992).

A Typical Meteorological Year (TMY) consisting of 12 typical meteorological months selected from various calendar months of a multi-year weather database became the preferred alternative to TRY and the standard weather data format for building performance simulations. The twelve months, typically taken from different years of record, are then concatenated by smoothing discontinuities through curve-fitting techniques to create an entire year. There are various methods for preparing a TMY (de Miguel & Bilbao, 2005; Festa & Ratto, 1993; Gazela & Mathioulakis, 2001; I. Hall et al., 1978; Lund & Eidorff, 1981): the Sandia method, which was initially developed in 1978 by Hall et al., is currently one of the most used approaches by the building energy simulation community (I. Hall et al., 1978). The National Renewable Energy Laboratory (NREL) recently updated this method into formats referred to as TMY2 in 1995 (Marion & Urban, 1995) and TMY3 in 2005 (Wilcox & Marion, 2008b).

Typical Weather Years (TWY) became widely used because they simplified the modeling process and reduced computational time while producing reasonably accurate predictions of the average building energy performance in the long term. Nevertheless, the use of TWY brings about some critical issues.

First, a typical year built upon historical data might not represent the present-day climate conditions, especially considering climate change. For example, Radhi reported that using a TWY based on data from 1961 to 1990 underestimated the electricity consumption in a central all-air HVAC system by approximately 14.5% for low-rise and high-rise commercial buildings in Bahrain compared to the predictions obtained using weather data from 1992 to 2005 (Radhi, 2009). The use of outdated weather files is particularly problematic for some parts of the world, such as Canada, which warms up at approximately twice the global average (Canada & Environment and Climate Change Canada, 2019). For instance, Kočí et al. (Kočí et al., 2019a) investigated the energy demand using current weather data sets from 2014 to 2017 compared to the test reference year (TRY) synthesized from the weather data between 1991 and 2005. The simulation results support the warming trend from 2013 to 2017, with heating demands 3.95% below the average and cooling demands 3.96% above the average compared with the Test Reference Year.

A second relevant issue is that different TWY developed through different methods existing in the literature might lead to diverging energy simulation outcomes (Bhandari et al., 2012a; Skeiker, 2007; Sorrentino et al., 2012), thus affecting the design decisions (Bevilacqua et al., 2019; Pernigotto et al., 2017).

Last but not least, a typical year is not appropriate for designing technical systems or sizing equipment because it neglects worst-case scenarios, i.e. extreme cold or hot weather conditions (D. B. Crawley & Lawrie, 2015). Indeed, a TWY cannot adequately reflect the fluctuations due to year-by-year weather conditions variability (D. Crawley, 1998). Therefore, a new approach to building performance simulation requires replacing a single-value energy prediction with a range that realistically represents building performance over various weather conditions. Recent improvements in computational power allowed overcoming these hurdles through multi-year simulations based on Actual Weather Years (AWYs), whose outputs reflect the building's response to the actual year-by-year variation in the climate conditions through an extended period. As a result, all energy use variations can be considered for optimal decision-making and avoid a preliminary selection procedure that may introduce errors or inaccuracy (D. Crawley, 1998). Presently, a limited number of research studies investigated the advantages of using the Actual Weather Years approach instead of the Typical Weather Year. One of the first studies showed that energy consumption in eight different office spaces in the U.S. varies between -11% to 7% in the 30-year actual weather dataset compared to the average multi-year weather dataset (D. Crawley, 1998). Cui et al. draw similar conclusions but with even a higher range of variation for the single-year results for a medium-sized office building in ten different cities in China (Cui et al., 2017). More recently, Evola et al. (Evola et al., 2021) used multi-year and typical-year approaches to investigate the energy use of an office building and a residential building in Catania, Italy. They discovered that TWY resulted in 10-35% and 15-25% underestimation in selecting the appropriate heating and cooling systems size.

This study aims to advance the knowledge about the use of different weather datasets for building energy modeling by addressing the following research questions:

- What is the impact of using TWY instead of AWY on the appraisal of the energy demand of different buildings' typologies under cold and warm climate conditions?
- What is the role of building features on the discrepancies between TWY and AWY-based energy predictions under cold and warm climate conditions?
- What are the advantages of performing multi-year simulations with AWYs instead of a single-year simulation with an adequate TWY?

To answer these questions, a complex university building and a typical single-family dwelling have been simulated with two typical weather years and ten actual weather years that refer to hourly weather data recorded by weather stations in a cold climate (i.e. Manitoba, Canada) and a warm climate (i.e. Catania, Italy).

First, the paper presents a comprehensive statistical analysis of the weather data recorded at the different sites. Then, it thoroughly discusses the discrepancies that the use of TWYs and AWYs determines in the results of dynamic energy simulations (heating and cooling energy demand, peak loads) between the two building types. To the best of the authors' knowledge, this is the first study to compare the impact of typical single-year and multi-year-by-year weather datasets on the building energy performance under two very distinct climates.

4.2 Methodology

4.2.1 Weather selection

The weather stations in both locations (Canada and Italy) are selected based on data availability over a ten-year timeframe from 2010 to 2019. This period is selected due to the dramatic changes in climate over the last decade seen worldwide, especially in Canada, which is warming at nearly twice the global rate (Canada & Environment and Climate Change Canada, 2019). Furthermore, Canada's weather station was also chosen based on its proximity to the modelled buildings. In this respect, Figure 13 shows that the Forks weather station is approximately 9 km from the case studies near the junction of the Red and Assiniboine rivers in Winnipeg, Canada. The Forks hourly data contained all the required parameters for energy modeling, including dry bulb temperature (°C), relative humidity (%), wind speed (m/s), wind direction (°) and atmospheric pressure (hPa), but not solar radiation. Therefore, solar radiation data were obtained from the National Solar Radiation Database (NSRDB) nsrdb.nrel.gov. Before using these data, they were statistically analysed and compared to weather data gathered from a rural weather station at Starbuck that measures solar irradiation around 35 km from the case studies. Considering that the agreement between the two datasets was reasonable (see Figure 13), we created all actual weather years using solar radiation data for the Forks location from NSRDB. The Italian weather data have been provided by the weather station owned by SIAS (Sicilian Agrometeorological Information System), situated 3 km south of the Fontanarossa airport of Catania. The SIAS weather station is placed in a rural area and overlooks the Mediterranean Sea on the east side while surrounded by agricultural fields on the north and the south side. The SIAS weather station is also near (about 300m) a light industrial and warehousing district on its west side. The SIAS weather data contained hourly values of all parameters needed for the whole-building energy modeling (Evola et al., 2021).

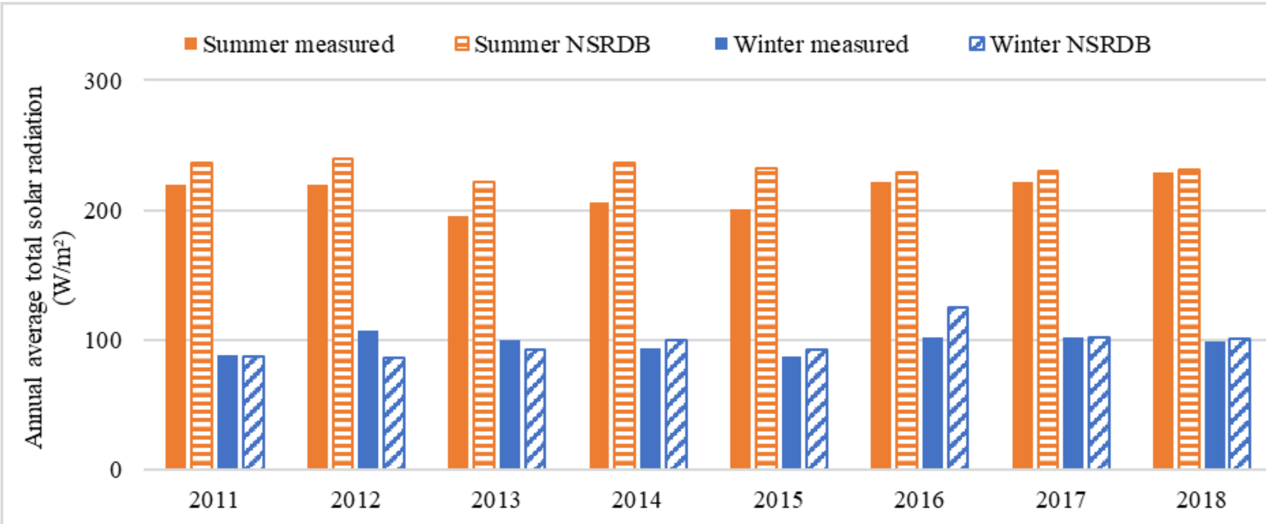


Figure 13: Comparison of the average annual measured and NSRDB total solar radiations for summer (October to April) and winter months (May to September) for Starbuck

Two most recent and widely used TWYs datasets developed through two consolidated procedures: TMY (first original version, aka Sandia's method (I. J. Hall et al., 1979)) and IWEC (Thevenard & Brunger, 2002), were selected for both locations resulting in four datasets, including CWEC (Canada), covering the 1998-2017 period, IWEC (Italy) containing 2002-2019 period, TMYx(15) for Canada and Italy comprising 2004-2018 period. Canadian Weather for Energy Calculations (CWEC) was developed by Environment and Climate Change Canada (previously Environment Canada) and the National Research Council as a Typical Year weather dataset for Canadian Locations. The CWEC is a weather dataset created based on the Sandia selection method (I. J. Hall et al., 1979). The representative meteorological months are selected from the Canadian Weather Energy and Engineering Datasets (CWEEDs). TMYx files are typical meteorological data derived from hourly weather data in the ISD (US NOAA's Integrated Surface Database) using the TMY/ISO 15927-4:2005 methodologies (*Climate.Onebuilding.Org*, n.d.). The TMYx files from both locations are available from the online repository climate.onebuilding.org. Table 5 summarizes the months used to generate the TWYs in Catania and Winnipeg.

Four typical and twenty actual weather years developed for both locations were arranged into a suitable format that can be read by building energy simulation tools. Amongst the various possible formats, the EnergyPlus weather file (.epw) was preferred due to its versatility and use with several established simulation programs, including DesignBuilder, TRNSYS, IES and ESP-r. The arrangement of the meteorological years into the .epw format required some additional parameters to those recorded by the local weather station. More information about the arrangement of the meteorological years and the procedure used to extract the typical months from the long-term weather dataset is available (Costanzo et al., 2020).

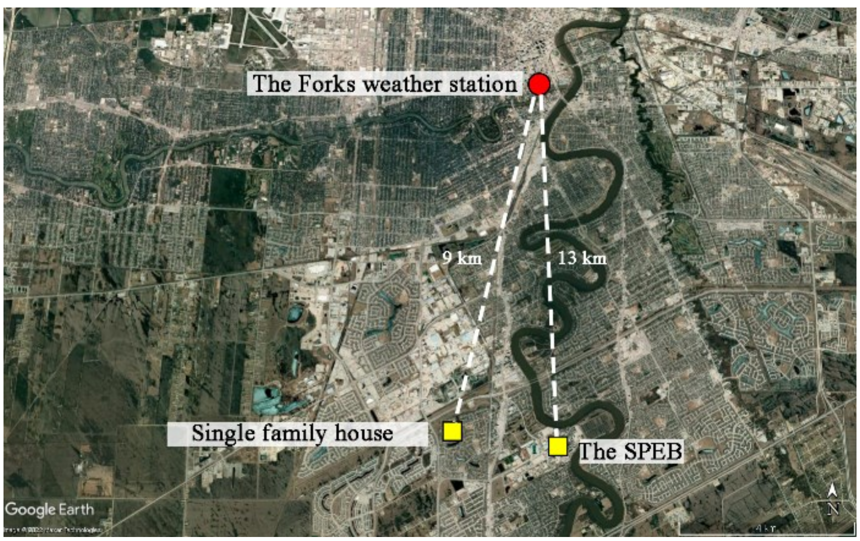


Figure 14: Location of the case studies

Table 5: Period selection of typical weather years based on different procedures

	TWY	Period	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Winnipeg	**CWEC**	**1998-2017**	2002	2009	2017	2011	2012	2011	2010	2015	2017	2008	2006	2009
	TMYx15	**2004-2018**	2015	2009	2017	2017	2017	2011	2017	2015	2006	2008	2006	2018
Catania	**IWEC**	**2002-2019**	2011	2006	2012	2019	2005	2009	2005	2007	2013	2015	2019	2008
	TMYx15	**2004-2018**	2014	2011	2013	2011	2010	2009	2004	2006	2014	2006	2018	2011

4.2.2 Building descriptions and modeling assumptions

To assess the impact of multi-year and typical year weather datasets on the energy performance of the building predicted by the building simulation tool Energy plus a complex university building called Stanley Pauley Engineering Building (SPEB) and a typical single-family house were selected. Both buildings located in Winnipeg, Canada (see Figure 14) are included in the analysis for the following reasons. First, their contrasting envelope systems, areas, schedules, and internal gains allowed estimating the difference in impact between the TWYs and AWYs on predicting the energy demand of two very different building models exposed to cold and hot climates. Second, since the SPEB is designed to meet LEED silver standard and the house was built before the first energy code, it enabled understanding of the importance of the impact of weather files on the highly-energy efficient building and the poorly performing house. Third, the university building has a curtain wall system and envelope architecture widely used worldwide in commercial and institutional buildings, including in the Mediterranean climate. Furthermore, even though the single-family house with its wood frame is typical for North America, there is an increase in the use of timber in the building sector across the world, including in Europe (Ramage et al., 2017). Consequently, the findings from analysing these two buildings could be of general interest and have implications for similar buildings elsewhere.

The university building is located at the Fort Garry campus of the University of Manitoba and has an orientation of 26° to the west of true north. It contains various space types, such as laboratories, student areas, fabrication spaces, offices, and meeting areas. Figure 15 a) shows that the SPEB has one floor below grade and three floors above grade, with a total area of 4,200 m^2. A bridge link connects the building to the Engineering and Information Technology Complex on the northside while it is adjacent to the existing Stanley Pauley Centre on the East side. Window to wall ratio is around 60%, with the most glazing on the South and West sides of the building. The building envelope system includes various high-performance envelope systems. In this respect, the exterior walls are made of concrete masonry on the outer layer (90mm x 90mm x 590mm) and concrete masonry unit (200 mm) on the inner layer separated by a 25mm air gap, two layers of board insulation (2x75mm) and vapor/air barrier membrane. Also, a 150 mm concrete slab is used for structuring the basement floor, and interior floors are made of 100 mm lightweight concrete. The roof is made of a concrete slab on the inner side with two layers of board insulation (150mm+100mm), a styrene-butadiene-styrene modified bitumen base and cap sheets with a roofing membrane on the outer layers. The windows include double glazing with a low-E outer glazing layer filled with argon (6-13-6 mm) and stainless-steel spacer.

As presented in Figure 15 b), the single-family house is a two-story structure with a total floor area of 185 m^2. The house was built in 1970, and it is oriented 27° to the west of true north. The house's layout includes three bedrooms, a kitchen and living room on the ground floor, two bathrooms, an insulated crawl space, a utility room, and ventilated open space at the basement level. The house does not have any windows on the east and west exterior walls, while the exterior north and south-facing walls feature 15% and 20% window-to-wall ratios. The exterior wall assembly features a conventional framing system (i.e., 2 x 4 wooden studs at 16" o.c.) with fiberglass batt insulation. Windows are double panes filled with air. The basement slab is made of 225 mm of concrete, and the floors are constructed of 19 mm of wood subfloor, 12.7 mm of sheathing and two layers of plywood (16 mm+12 mm). In the case of the roof, the plywood (16mm) and the roof sheathing (13mm) are separated by ceiling air space resistance, while the asphalt shingles constitute the outer layer. Table 6 summarizes the overall thermal resistances (U-values) of the envelope components of both buildings.

Table 6: U-factor of envelope components

U-value (W/m² K)	SPEB	House
Basement slab	0.271	1.674
External walls	0.263	0.288
Floor	3.445	1.568
Roof	0.135	0.14
Glazed surfaces	1.666	2.4

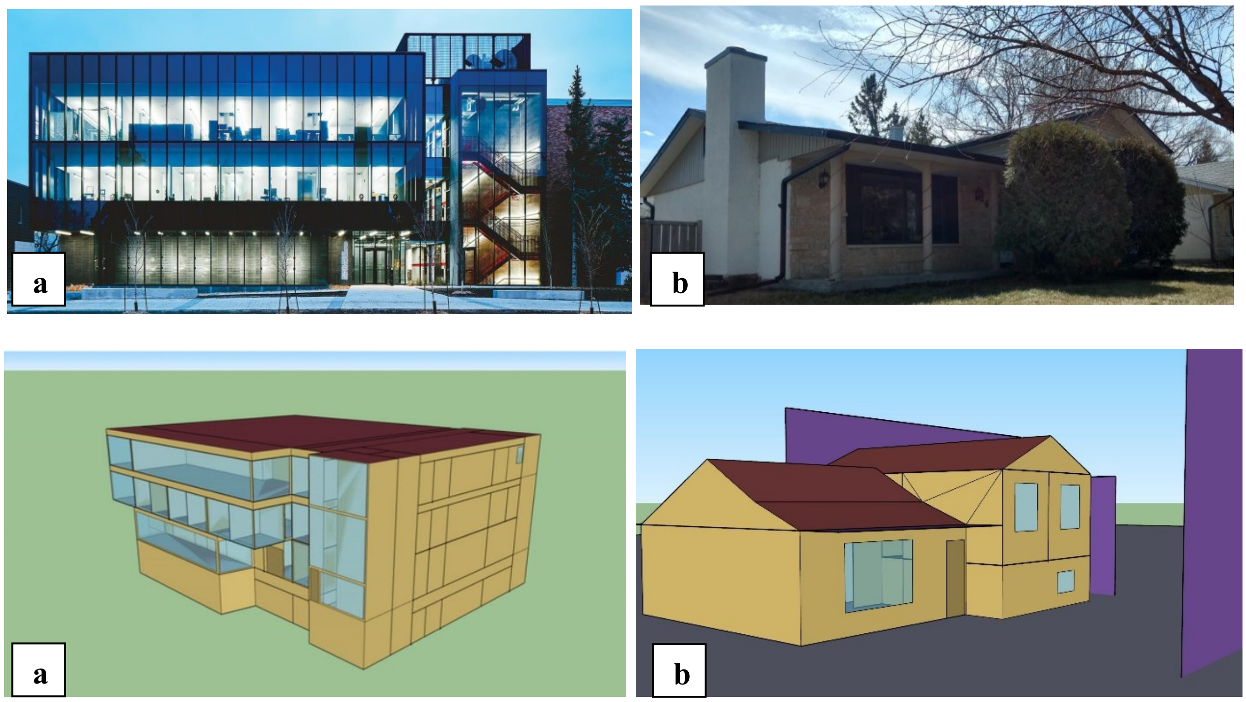


Figure 15: Actual buildings and building energy models of the SPEB (a) and the single-family house (b)

Both buildings' heating and cooling loads are estimated using an ideal load air system scenario. The ideal load air system is an object intended to deliver heating and cooling to a zone with 100 percent effectiveness at all times to meet any heating or cooling requirement of the zone. This scenario, alongside with free float scenario, is intended to evaluate the geometry, the envelope materials, and performance of a building without modeling an entire HVAC system. Considering that the two buildings have different HVAC systems, such an approach was needed. For example, the SPEB has a complex and high-performance radiant floor system coupled with the two-pipe fan-coils and a dedicated outdoor air system (Al-janabi et al., 2019), whereas the house has a simple non-efficient forced-air system (Ramage et al., 2017). Therefore, the ideal load air system scenario allowed the comparison of the impact of the weather files on the models' predictions without implications for the HVAC systems' performances. The exclusion of HVAC systems also resulted in the lighter models significantly decreasing the computational time. That strategy was especially significant for the SPEB, composed of 97 thermal zones (see Figure 17). The single-family house contains 9 thermal zones (see Figure 16). Furthermore, Table 7 summarizes the internal heat gains and the schedules of setpoint and setback temperatures for the SPEB and the single-family house.

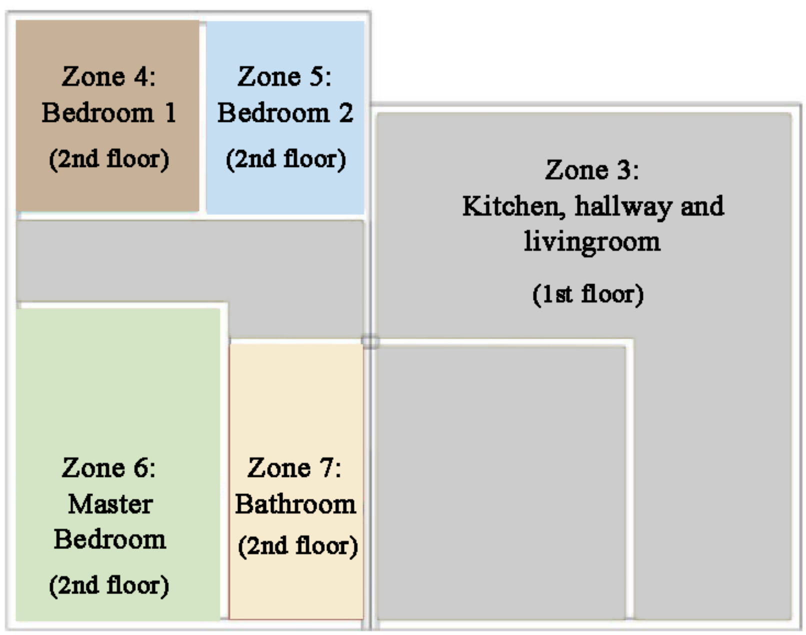


Figure 16: Thermal zones of the single family house

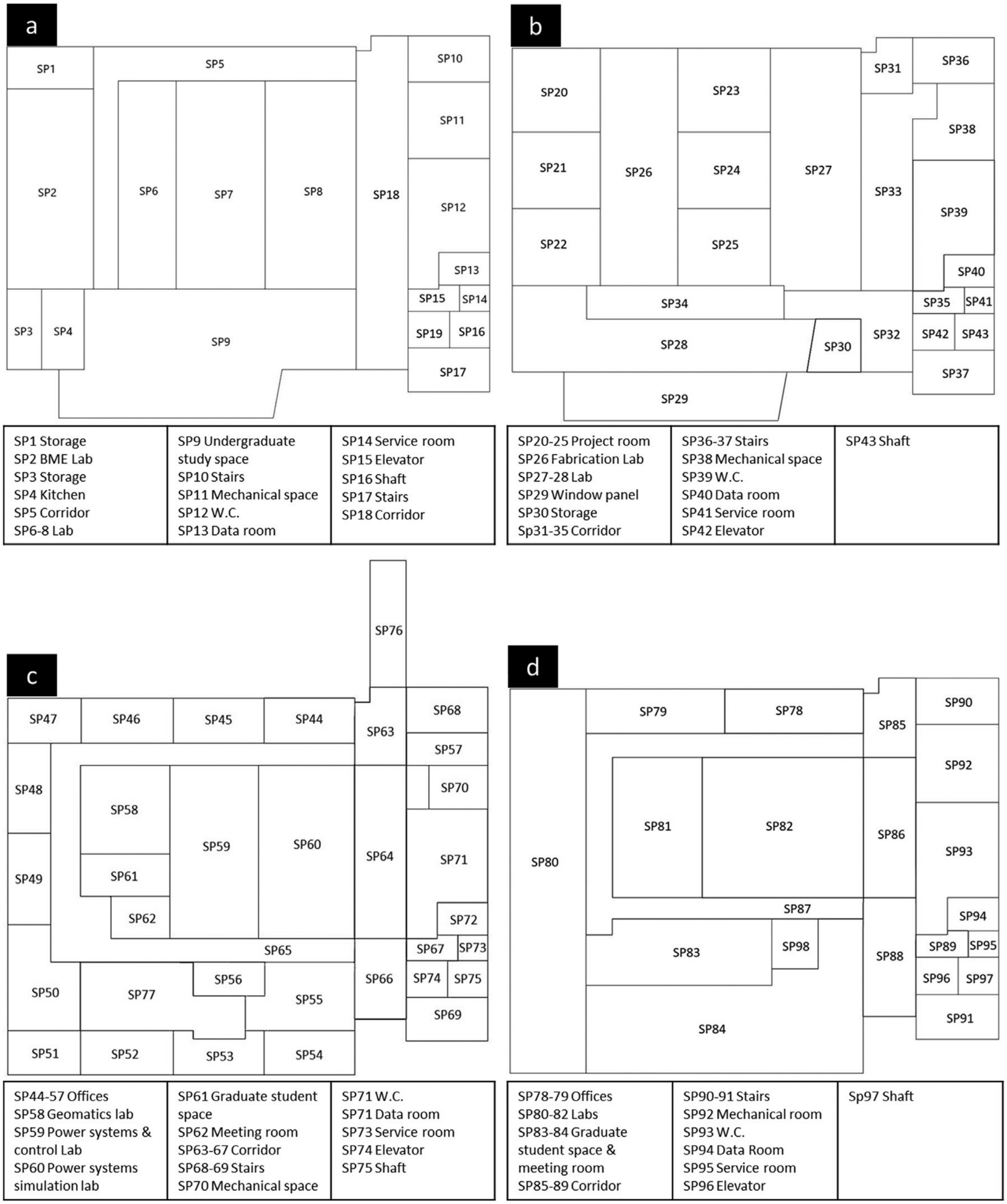


Figure 17: Thermal zones of the Stanley Pauley Engineering Building (SPEB): (a) Basement, (b) First Floor, (c) Second Floor, and (d) Third Floor

Table 7: Internal heat gains, schedules, infiltration, and ventilation rates

	SPEB	House
Lighting and plug loads	1.37 - 24.434 W/m^2	1.052 W/m^2
People occupancy	0.1 - 0.54 person/m^2 (medium office activity: 120 W/person)	0.019 person/m^2 (Sedantry activity: 108 W/person)
Heating setpoint	Weekdays 20°C (06:30 am-10:30 pm), weekends 18°C (24 h)	20°C every day (24 h)
Heating setback	18°C (24 h)	NA
Cooling setpoint	Weekdays 24°C (06:30 am-10:30 pm), weekends 26°C (06:30 am-10:30 pm)	26 °C every day (24 h)
Cooling setback	28°C (24 h)	NA
Infiltration rate (flow/exterior surface area)	0.0003 $m^3/s\text{-}m^2$	0.0005 $m^3/s\text{-}m^2$
Ventilation rate	-	-

This research employs the Mean Bias Error (MBE) and the Root-Mean-Square Error (RMSE) to effectively compare the results of simulations based on a typical year to those of multi-year simulations. As a result, these are described as seen in the equations (1) and (2): "x" corresponds to a particular Typical Weather Year and "i" refers to each actual year, and n is equal to 10, which is the number of studied actual weather years.

$$(1) \qquad MBE = \frac{\sum_{i=1}^{10}(Q_{H_x} - Q_{H_i})}{10}$$

$$(2) \qquad RMSE = \sqrt{\frac{\sum_{i=1}^{10}\left(Q_{H_x} - Q_{H_i}\right)^2}{10}}$$

The equations above refer to the energy demands for space heating (Q_H), but they can also be written concerning the energy demands for space cooling (Q_C).

The assessment of SPEB and house models' predictions included inter-model comparison and validation of models of different complexities. In this respect, the single-house model with HVAC systems was developed and validated against the measured energy consumption (Mobeen et al., 2018). Similarly, three different versions of the SPEB model, including free-float, ideal air system, and detailed, were developed in EnergyPlus and verified using inter-model comparison with the SPEB models developed in IES by consulting company Stantec Inc. for compliance with the building energy code (Al-janabi et al., 2019). The ideal air system models used in this study represent a modified detailed model of the house and a modified ideal air load system of the SPEB. The modifications of the models included adding internal heat gains as defined in detailed models of the buildings to provide realistic predictions of heating and cooling loads and peaks under two different climates. Furthermore, changes in setpoint temperatures were introduced to reasonably represent true-to-life indoor conditions under both climates.

4.3 Results and discussion

4.3.1 Weather data

This section analyses the meteorological data collected by the Forks weather station in Winnipeg, Manitoba, and the SIAS weather station in Catania, Italy, from 2010 to 2019 and compares it to the statistical distribution of typical weather years produced from the same dataset for each climate. The statistical analyses included four main weather parameters with the most significant impact on buildings' energy performance (i.e., dry-bulb air temperature, global horizontal irradiance, relative humidity, and wind speed) and heating and cooling degree days. For conciseness, Figures 18-21 present the boxplots of the coldest month (January) and the warmest (July). Additionally, Figure 22 compares heating and cooling degree days between multi-year distributions and typical weather years for both locations.

Figure 18 illustrates that cold Winnipeg experienced a significant monthly temperature variation (≈ 42 °C) in January across ten-year period with dry-bulb air temperature ranging from -34.6 °C (2019) to 7.3 °C (2012). In contrast, the significantly warmer and within the narrower range (22.4

°C) Januarys in Catania had dry-bulb air temperatures ranging between 0.4 °C (2012) and 22.8 °C (2016). Furthermore, while Winnipeg experienced the coldest January in 2014 with a mean dry bulb temperature of -19.4 °C, in Catania, January 2014 was the second warmest with an average dry bulb temperature of 11.7°C after January 2018 with 12.6 °C. The warmest January in Winnipeg was January 2012, with an average of -8.3 °C. Similarly, January 2012 was the third warmest in Catania with 10.1°C after January 2017 and 2019 with 9.1 °C and 9.2 °C, respectively. Over the ten years, heating-dominated Winnipeg had a higher average dry-bulb air temperature fluctuations in January than cooling-dominated Catania. Thus, the mean temperature of AWYs in Catania varied between -1.7 °C and 1.8 °C compared to the average temperature over the ten years. For Winnipeg, the mean temperature of AWYs fluctuated significantly more than Catania, between 4.5 °C and 4.1 °C.

Furthermore, in Winnipeg, the mean dry-bulb temperatures of -12.7 °C and -12.5 °C of the TMY and CWEC were approximately 1 °C (≈ 7.8%) higher than the average of the ten-year actual weather data (≈ -13.6 °C). Considering that the minimum dry-bulb temperatures of the TMY and CWEC were around 2.7% lower than the ten-year average, this discrepancy between the typical and actual weather years is due to approximately 31% higher maximum dry-bulb air temperatures of TWYs than AWYs (≈ 3.6 °C). On the other hand, in Catania, the mean dry-bulb temperature of TWYs was around 3.5% lower than the ten-year average of approximately 10.8 °C. The dry-bulb air temperature has been relatively stable over the years for both climates in July, with 2012 as the warmest. Comparable to the winter month, the temperature distribution was more extensive in Winnipeg than in Catania during the warmest month. Thus, the mean dry-bulb air temperature in July varied between 0.7 °C and -1.1 °C compared to the ten-year average in Catania. In Winnipeg, this temperature fluctuation in July was between 2.4 °C and 1.7 °C. In contrast to January, in July, typical weather years better agreed with the actual years of both locations.

Figure 19 a) displays that Winnipeg's global horizontal irradiance (GHI) in January ranged from 116 Wh/m² (2017) to 2399 Wh/m² (2015) and in July from 1522 Wh/m² (2010) to 8669 Wh/m² (2011). Figure 19 b) presents that Catania's GHI ranged from 180 Wh/m² (CWEC) to 3809 Wh/m² (2017) in January and from 2509 Wh/m² (2012) to 8401 Wh/m² (2010). With a mean annual global horizontal irradiance (GHI) of 3634 Wh/m² over ten years, Winnipeg received around 24% less solar energy than Catania with 4775 Wh/m². During July, Winnipeg, with a mean GHI of 6823 Wh/m², received only around 8% less solar energy than Catania, with 7443 Wh/m². However, Catania experienced approximately 52 % higher solar energy during January with a mean GHI of 2454 Wh/m² compared to Winnipeg with 1171 Wh/m². Furthermore, in January, Winnipeg had a smaller interquartile range and lower differences between minimum and maximum values than Catania. Figure 19 b) illustrates that in July, the GHI distribution for Catania shifted towards higher values, and the boxplots show a smaller interquartile range due to the condensed data. Although the average global horizontal irradiance in July was higher for AWYs of Catania, Winnipeg experienced higher peaks for all actual years. Also, outliers for Catania's GHI data suggest the incidence of cloudy days and humid air, which adversely impacted solar irradiance.

Figure 20 shows that the distribution of the relative humidity is almost symmetrical for all the years in both climates. Nevertheless, Catania data exhibit more significant dispersion in January and July compared to Winnipeg. In January, Winnipeg's mean relative humidity varied between 71.2% and 78.6%, while Catania's ranged from 66.6% to 77.6%. In July, Winnipeg had relative humidity between 58.2% and 67.0%, whereas this range for Catania was between 49.6% and 61.5%. In both climates, CWEC/IWEC showed higher mean relative humidity in January than

TMY. However, the difference of 7% was more significant for Winnipeg compared to only 1.4% in Catania. In July, CWEC was again more humid in Winnipeg than TMY, with 2.4% higher mean values. In contrast, TMY for July in Catania had 11.6% higher average humidity than IWEC.

In Winnipeg, the yearly variance in environmental parameters between the TWY and ten actual weather years (AWY) is the most significant for the wind speed (see Figure 21). CWEC and TMY, with annual mean wind speeds of 2.1 and 2.08 m/s, respectively, had around 73 % lower mean annual wind speed than ten AWYs with wind speeds ranging from 6.54 to 9.4 m/s. The wind speed study of Catania shows a slightly increasing tendency during the ten years in all months. Furthermore, the mean annual wind speed of TMY is approximately 35% higher than measurements from SIAS meteorological station and around 31% above the ten-year average. These findings suggest that the wind speed measurements from SIAS meteorological station better resemble the recent actual weather data on the Catania location.

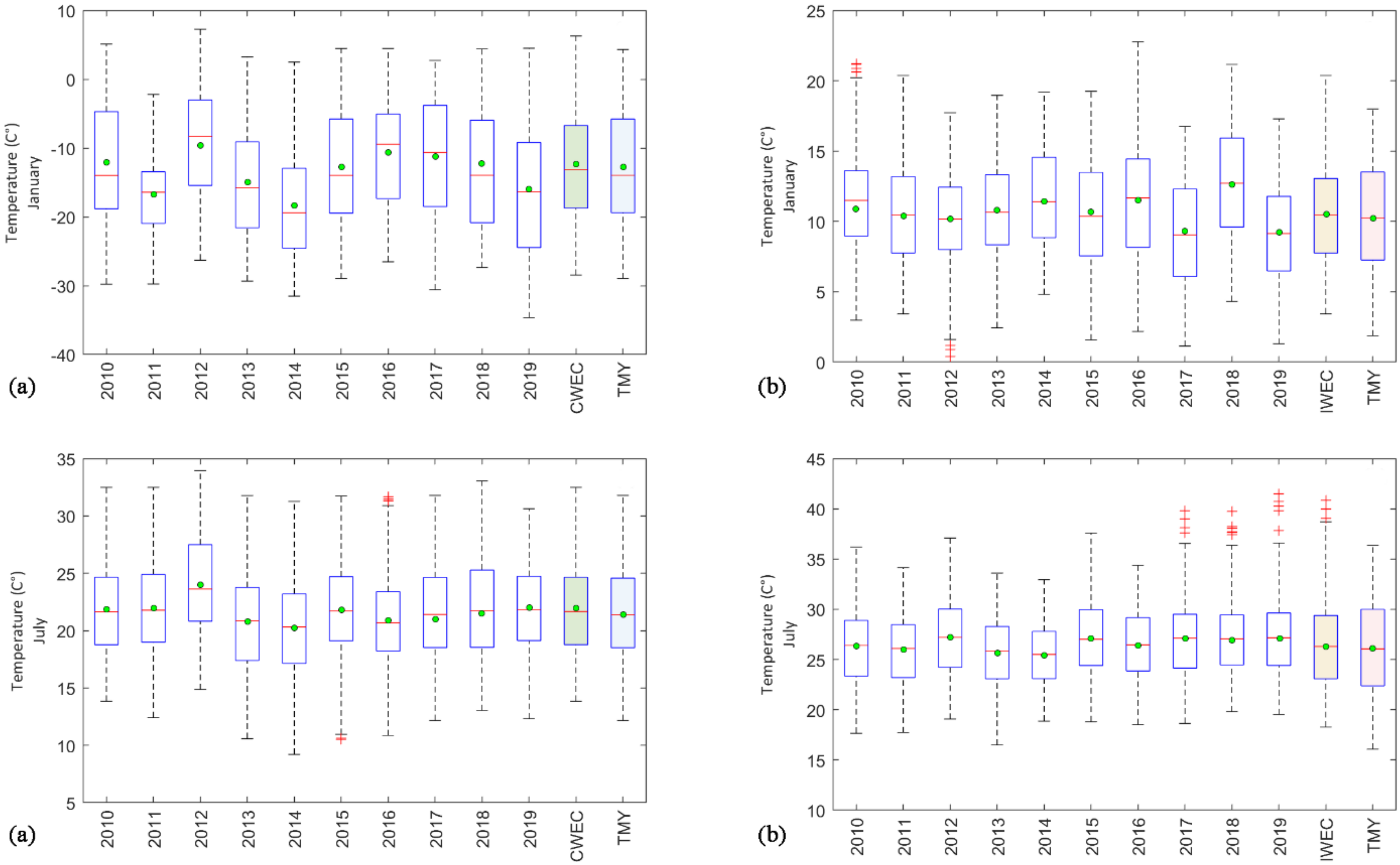


Figure 18: Distribution of the outdoor dry bulb temperature. (a) Winnipeg, (b) Catania

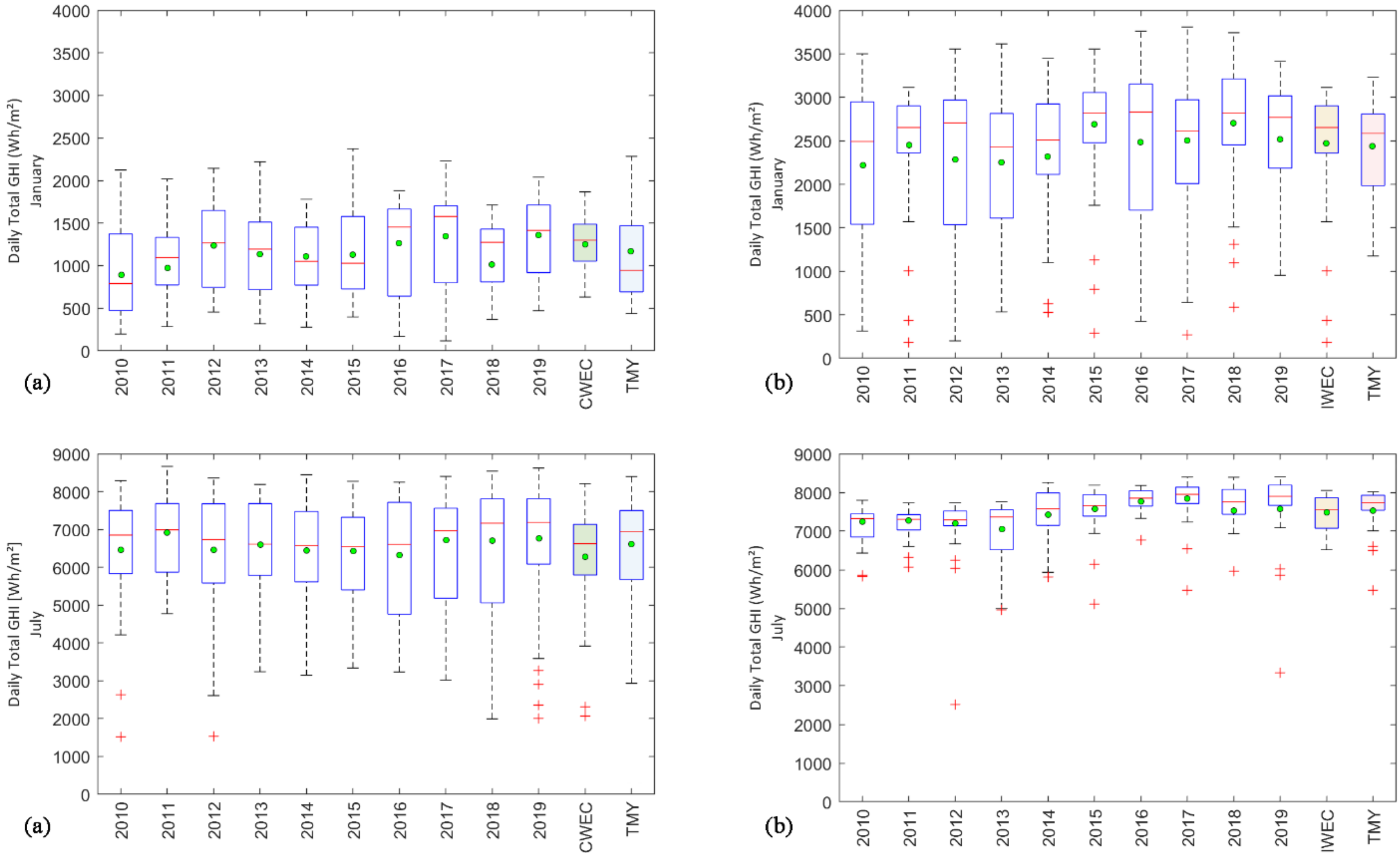


Figure 19: Distribution of the global horizontal irradiance. (a) Winnipeg, (b) Catania

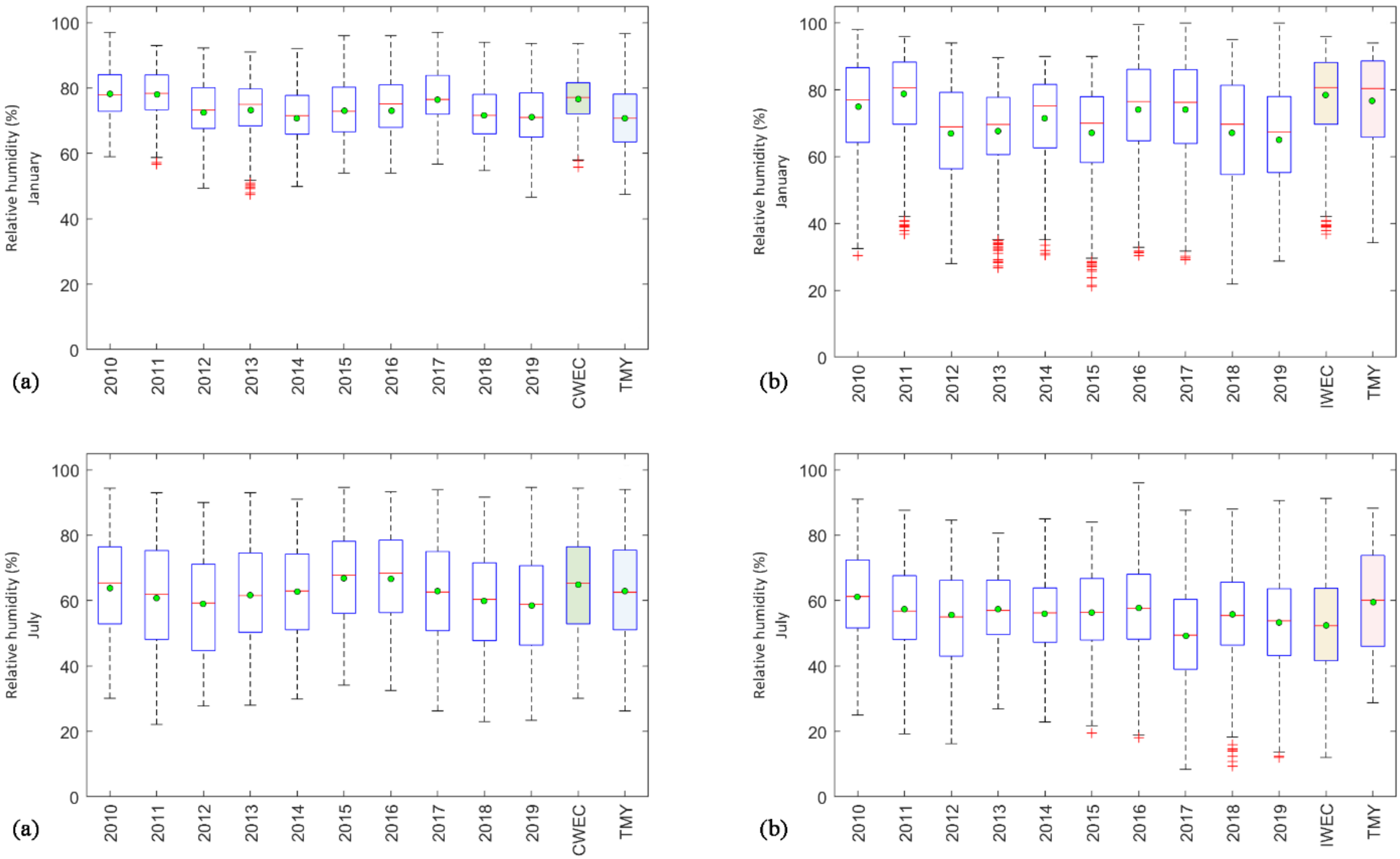


Figure 20: Distribution of relative humidity. (a) Winnipeg, (b) Catania

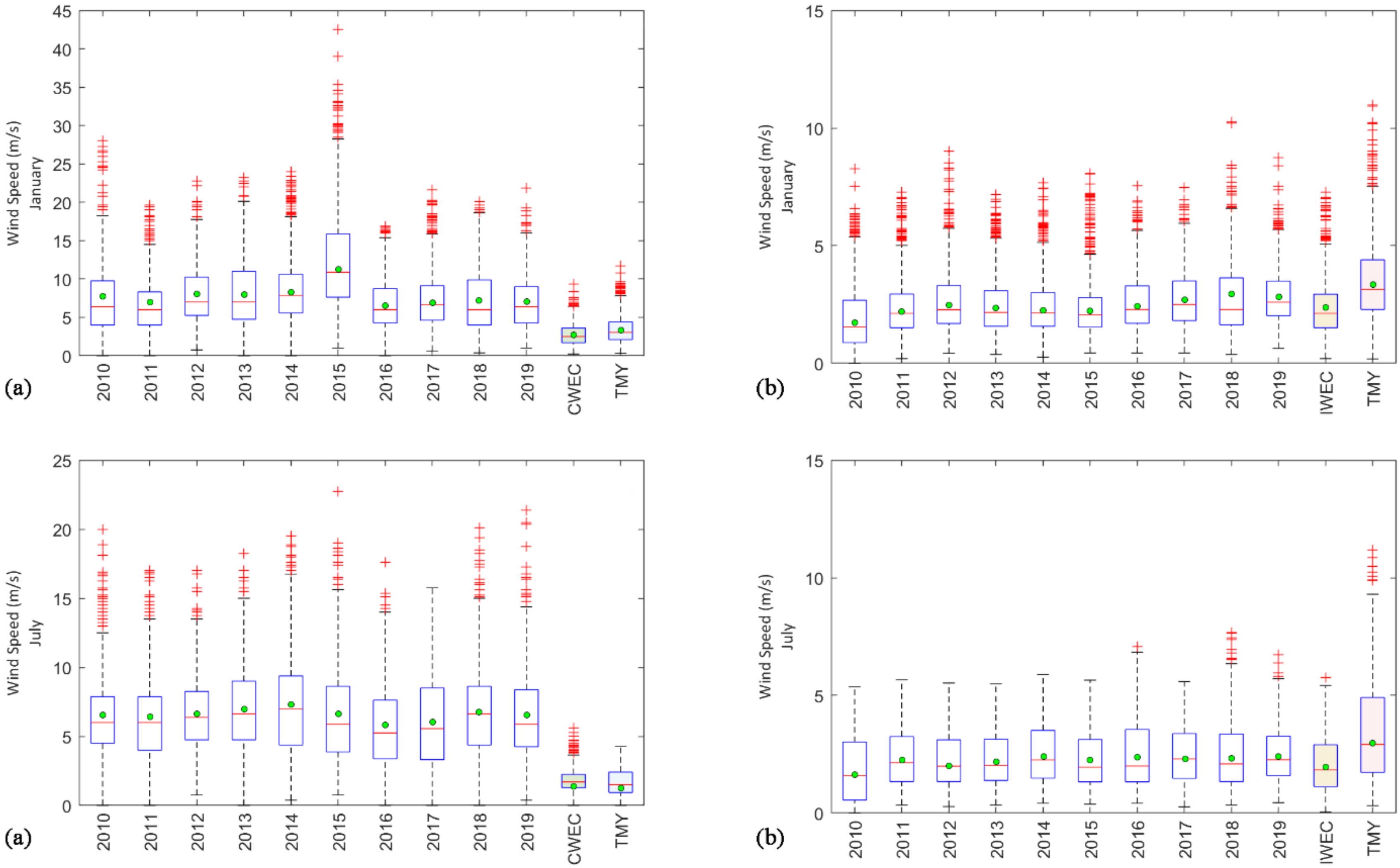


Figure 21: Distribution of the wind speed. (a) Winnipeg, (b) Catania

Figure 22 presents the annual heating degree days based on 18 °C (HDD18) and cooling degree days based on 23 °C (CDD23) to provide a detailed look at the variation in actual weather data for recording years from 2010 to 2019. Heating-dominated Winnipeg exhibited a drastically higher number of HDD ranging from 4534 (2010) to 5774 (2014) than CDD ranging from 13 (2016) to 58 (2012). On the other hand, Catania had more balanced needs for heating and cooling, with HDD ranging from 746 (2016) to 1031 (TMY) and CDD ranging from 221 (2010) to 360 (2019). Therefore, Winnipeg experienced around 83% more heating degree days than Catania, while Catania had approximately 88% more cooling degree days than Winnipeg.

Considering the HDD in Winnipeg, the TMY weather data is very close to the median of the ten-year actual weather data, while the CWEC exceeds the median by 2.5%. Figure 22 also shows that, unlike Winnipeg, HDD for TMY weather file is outside the range of HDD distribution for the yearly SIAS values in Catania, surpassing the median by 15%. However, IWEC weather data is almost equal to the median of Catania AWYs distribution with less than a 1% difference.

Regarding the CDD, the TMY and CWEC weather data remained in the second and the third quartiles of the long-term distribution of Winnipeg, respectively. However, TMY is 17% below the median of the multi-year distribution, while CWEC is about 7% above. In Catania, the cooling degree days of both TWYs are close to each other, and they are about 6% below the long-term median. These results suggest that CWEC for Winnipeg is more reliable than TMY in dynamic simulations for predicting the cooling demand; however, TMY better describes the current weather conditions than CWEC weather data for predicting the heating demand of the building. For Catania, IWEC weather data better depict the current weather conditions than TMY.

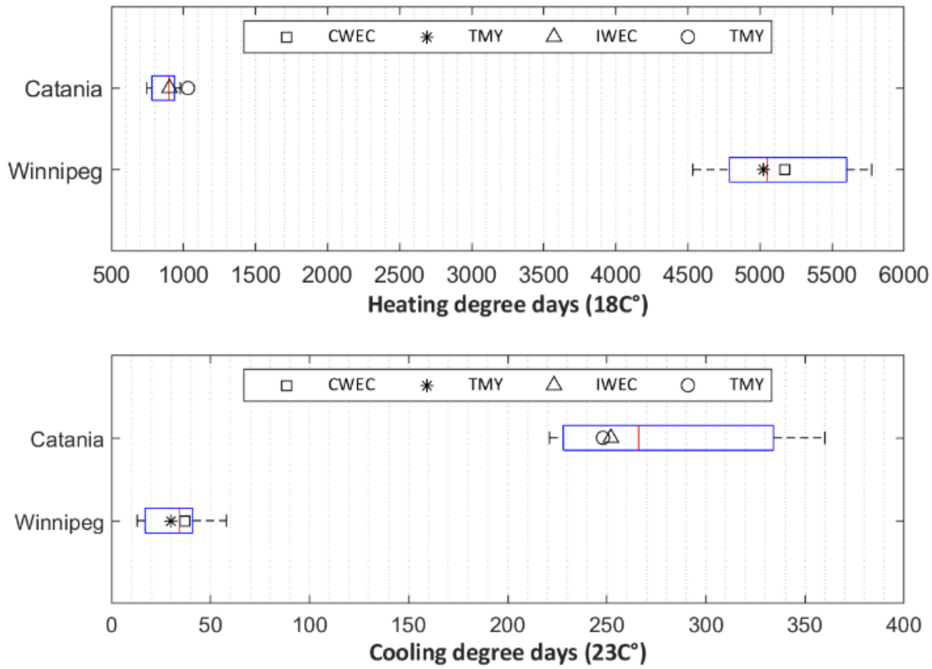


Figure 22: Heating degree days and cooling degree days. Note: comparison between multi-year distributions and single typical weather years

4.3.2 Energy simulation

Figure 23 shows the multi-year boxplot distributions of heating and cooling energy use intensity of the university building and single-family house and the geometric shapes that present their energy performance under the typical weather year data for two climates. The two buildings exhibit different space energy consumption patterns concerning the climate. The heating demand distribution for the SPEB under the Winnipeg climate skews positively and varies between 36 kWh/m² and 54 kWh/m². Heating demand distribution for the residential house under the Winnipeg climate also skews positively, but with significantly higher extremes ranging from 115 to 135.7 kWh/m². In contrast, the SPEB's cooling energy demand between 23.33 and 29.72 kWh/m² is around 96% higher than a single-family house, ranging from 0.48 to 0.93 kWh/m². Under Catania's climatic conditions, the house, with an average of 29 kWh/m², consumed around 76% less energy for space conditioning (heating and cooling) than in Winnipeg, with 124 kWh/m². On the other hand, the SPEB in Catania, with an average of 71.6 kWh/m², used almost equivalent energy for space conditioning as in Winnipeg, with 71.1 kWh/m². Both buildings consumed less space heating energy under Catania's than Winnipeg's climatic conditions. Thus, the SPEB in Catania, with a range from 0.58 to 1.22 kWh/m², had a 98% lower heating energy demand than in Winnipeg. Similarly, the single-family house in Catania, with a range between 6.9 and 9.3 kWh/m², exhibited around 93% lower heating energy demand than in Winnipeg. In contrast, both buildings experienced significantly higher cooling needs under Catania's than Winnipeg's weather conditions. In particular, the SPEB exhibited high cooling needs under the cooling-dominated Catania's climate ranging from 68.17 to 72.64 kWh/m². The house's cooling needs in Catania ranged from 18.8 to 23.2 kWh/m².

The likely reason for the lower heating demand of the university building than the single-family house under Winnipeg's climatic conditions is SPEB's significantly higher internal heat gains and window to wall ratio, especially on the southern exposure (see Table 6 and Figure 17). On the other hand, these features of the university building resulted in higher cooling needs than the house during sunny Winnipeg's summer months (see Figure 19). Similarly, a large glazing area (~ 60%) coupled with internal loads of the SPEB negatively impacted cooling requirements in cooling-dominated Catania. At the same time, a large glazing area is also the likely explanation for significantly higher heating needs of SPEB during cold months in Winnipeg than during mild winters in Catania (see Figures 18, 19 and 22).

Concerning the typical weather years (see Figure 23), CWEC and TMY for Winnipeg fall outside the interquartile multi-year heating and cooling distribution ranges. In this respect, the SPEB's space heating energy predictions with TMY and CWEC were 11.3% and 8.2% below the ten-year median of 43.4 kWh/m², respectively. The single-family house's space heating energy predictions with TMY and CWEC were 3.6% and 2.7% below the ten-year median of 122.9 kWh/m², respectively. In contrast, CWEC and TMY overpredicted the cooling demand for the university building in Winnipeg by 10.5% and 13.8% compared to the ten-year median of 26.7 kWh/m². The discrepancy between the cooling demand predictions of TWYs and AWYs was more significant for the house than for SPEB due to the house's low cooling energy needs under Winnipeg's climate. Thus, CWEC and TMY overpredicted the cooling demand for the single-family house in Winnipeg by 69.3% and 82.4% compared to the ten-year median of 0.69 kWh/m². Regarding Catania, TWYs underestimated cooling demand compared to the ten-year median, and this discrepancy was more significant for TMY than IWEC. Thus, Figure 23 shows that the SPEB's space cooling energy predictions with TMY and IWEC were 6.5% and 1.8% below the ten-year median of 71.7 kWh/m², respectively. Similarly, the house's space cooling energy predictions with TMY and IWEC were 8.7% and 3.3% below the ten-year median of 21.0 kWh/m², respectively. While the two TWYs were inconsistent between the building types concerning heating demands, similar to cooling, the difference between predictions was higher for TMY than IWEC. Thus, the SPEB's space heating energy predictions with IWEC were 2.6% below the ten-year median of 0.91 kWh/m², whereas TMY overpredicted by 82.4%. In contrast, both TWYs overpredicted the heating demand of the house compared to the ten-year median of 8.2 kWh/m² (2.8% by IWEC and 27.4% by TMY). These results show that TWYs, on the one hand, tend to underpredict the dominant energy demand and, on the other hand, overpredict the minor energy demand in both climates compared to ten-year actual data. Such predictions might lead to inadequate design and sizing of the HVAC equipment and the performance gap between the modelled and actual performance of the buildings.

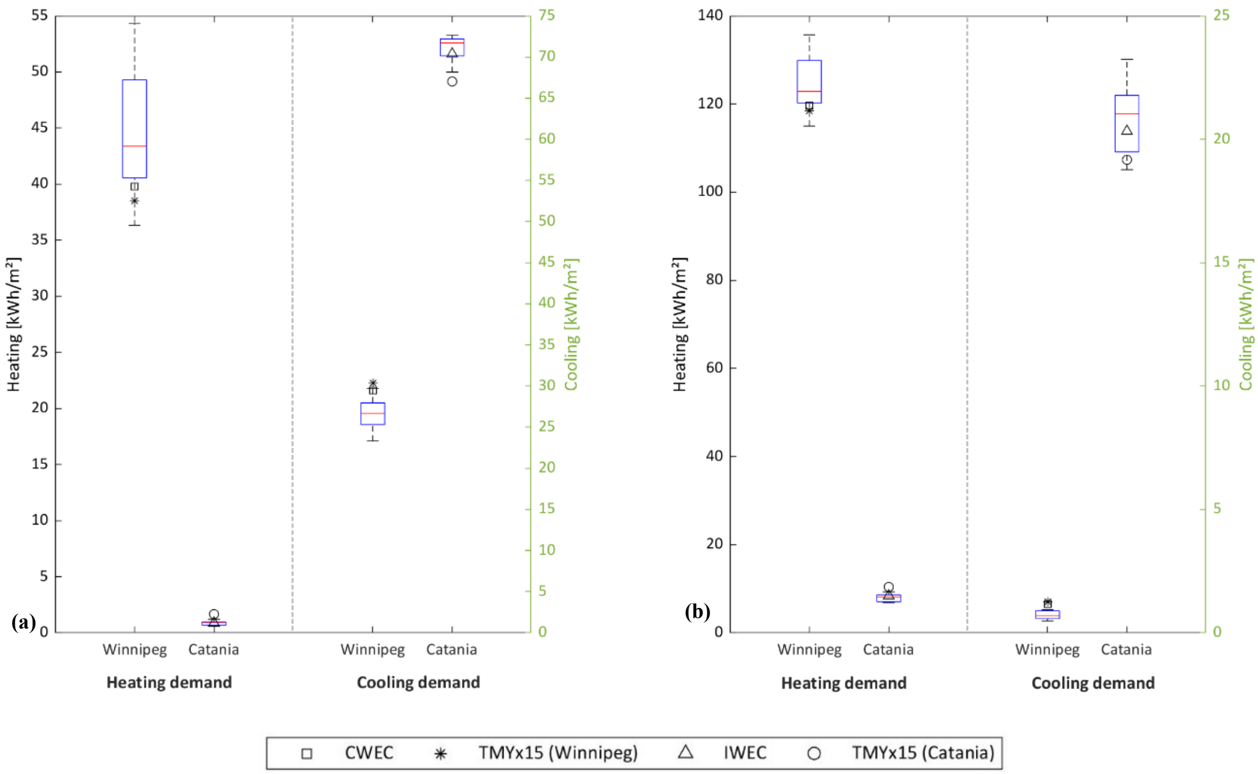


Figure 23: : Heating and cooling energy intensity in Winnipeg and Catania of (a) SPEB (b) single-family house. Notes: the boxplots represent the multi-year distribution, and the shapes on the charts show the actual value for the typical weather year data.

Figure 24 illustrates the multi-year boxplot distributions of heating and cooling peak loads of the university building and single-family house and the geometric shapes that present peak load predictions under the typical weather year data for two climates. Both buildings had more considerable variability of heating and cooling peak loads in Winnipeg than in Catania. Thus, the SPEB's cooling peak load distributions were positively skewed, ranging from 106.6 to 144.7 kW in Winnipeg while from 152.2 to 160.3 kW in Catania. The single-family house experienced cooling peaks from 0.85 to 1.62 kW in Winnipeg, whereas from 2.36 to 2.79 kW in Catania. The negatively skewed SPEB's hating peak loads ranged from 170.8 to 204.3 kW in Winnipeg, while in Catania, from 23.6 to 45.5 kW. The house's heating peak loads in Winnipeg ranged from 5.7 to 6.5 kW, and they were between 1.69 and 1.90 kW in Catania. The likely reason for the higher dispersion of heating and cooling peak loads in Winnipeg than in Catania is more variable weather conditions in Winnipeg, as presented in Figures 3 to 6, which particularly impacted a highly-glazed university building.

Regarding typical weather years, the SPEB's heating peak load predictions with CWEC and TMY were 5.0% and 8.9% below the ten-year median of 194.9 kWh/m² in Winnipeg, respectively. With a similar difference in the opposite direction, the SPEB's cooling peak load predictions with CWEC and TMY were 8.6% and 6.1% above the ten-year median of 125.2 kWh/m² in Winnipeg, respectively. The house model predictions with TWYs of Winnipeg were closer to the ten-year median. Thus, both typical weather years underpredicted heating peak loads of the single-family house by 3.04% compared to the multi-year median of 6.09 kW. Furthermore, CWEC also had a 3.70% lower, whereas TMY had a 7.0% higher cooling peak load prediction than the ten-year median of 1.22 kW. For the SPEB under Catania's weather conditions, both typical weather years predicted close, in the range of 0.7-2.7% to the ten-year median of 31.4 kW for heating peak loads and 156.4 kW for cooling peak loads, except for IWEC overestimating median heating peak load by 14.2%. Similarly, concerning the single-family house, TWYs predicted in the range of 2.01-4.25% to the ten-year median of 31.4 kW for heating peak loads and 156.4 kW for cooling peak loads, except for IWEC overestimating median heating peak load by 8.2%. These findings provide further evidence of the discrepancy between TWYs' and AWYs' predictions that could lead to inappropriate design and sizing of HVAC systems and the inability of technical systems to provide thermal comfort under the worst-case scenario.

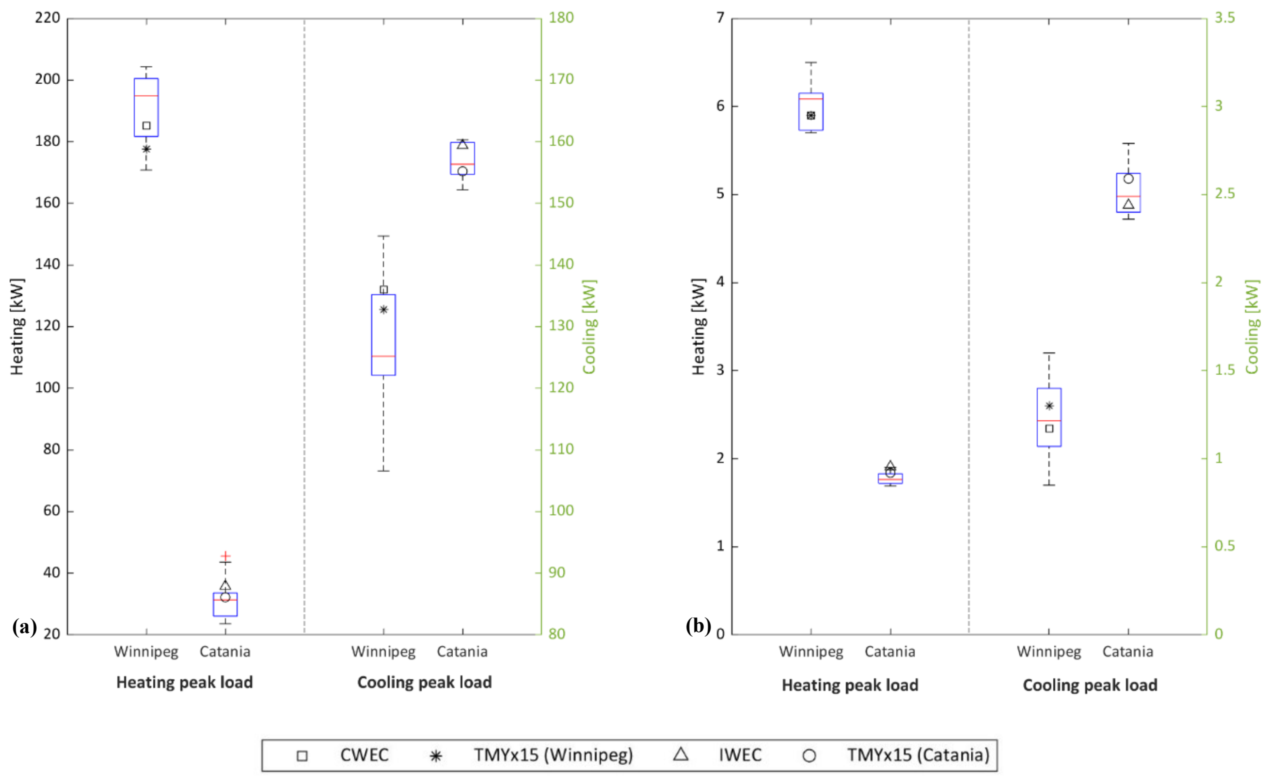


Figure 24: Heating and cooling peak loads in Winnipeg and Catania of (a) SPEB and (b) single-family house. Notes: the boxplots represent the multi-year distribution, and the shapes on the charts show the actual value for the typical weather year data.

Further understanding required analyses of the monthly energy use of both buildings under two climates, shown in Figure 25. For conciseness, we presented the boxplot distributions of monthly variation in space conditioning loads (sum of heating and cooling) of the SPEB and house under Winnipeg's and Catania's climatic conditions. Overall, both buildings exhibited wider dispersion of space conditioning loads in Winnipeg than in Catania due to Winnipeg's more significant variation in parameters that considerably impact the building's energy demand, such as outdoor air temperature and solar radiation (see Figures 18 and 19). Hence, the interquartile range of the SPEB is from 0.32 to 3.14 kWh/m² in Winnipeg and from 0.26 to 0.88 kWh/m² in Catania. Similarly, the interquartile range of the house is from 0.28 to 3.76 kWh/m² in Winnipeg and from 0.06 to 0.89 kWh/m² in Catania. Unlike in Catania, the distinct difference in the space conditioning patterns between the buildings in Winnipeg is related to the higher cooling needs of the SPEB than the house during the summer months. On the other hand, while the two buildings have similar patterns under Catania's weather, during some months, they behave differently. For instance, the SPEB had the highest space conditioning use in April during the spring season, whereas the house had the lowest during this month. The analysis of heating and cooling loads showed these results could explain the high solar radiation in April that increased cooling energy consumption of the highly-glazed university building.

Typical weather years were within the interquartile range most of the months through tough the year for both buildings and climates. Also, the discrepancy between the predictions of space conditioning between the typical files was less than 7% for most months for the buildings in Winnipeg and the only month with a difference of 18% was December. The analysis of the environmental parameters of the two typical weather files showed that CWEC had a 30% lower average monthly dry-bulb temperature than TMY, which resulted in higher predictions of energy consumption (see Figures 25 a) and c). For SPEB in Catania, the gap between two typical years was between 0.4% and 6.3% for all months except May, with approximately 14% higher prediction of IWEC than TMY. The analysis of weather parameters and space energy consumption showed that the likely reason is the 100% higher average wind speed in May of TMY than IWEC, which increased convective heat losses and thus reduced cooling energy consumption in the university building. The monthly discrepancy between IWEC and TMY was significantly higher in the case of the single-family house, ranging from 0.55% in August to 63.33% in May. The higher discrepancy between the two years occurred in months with low space energy consumption.

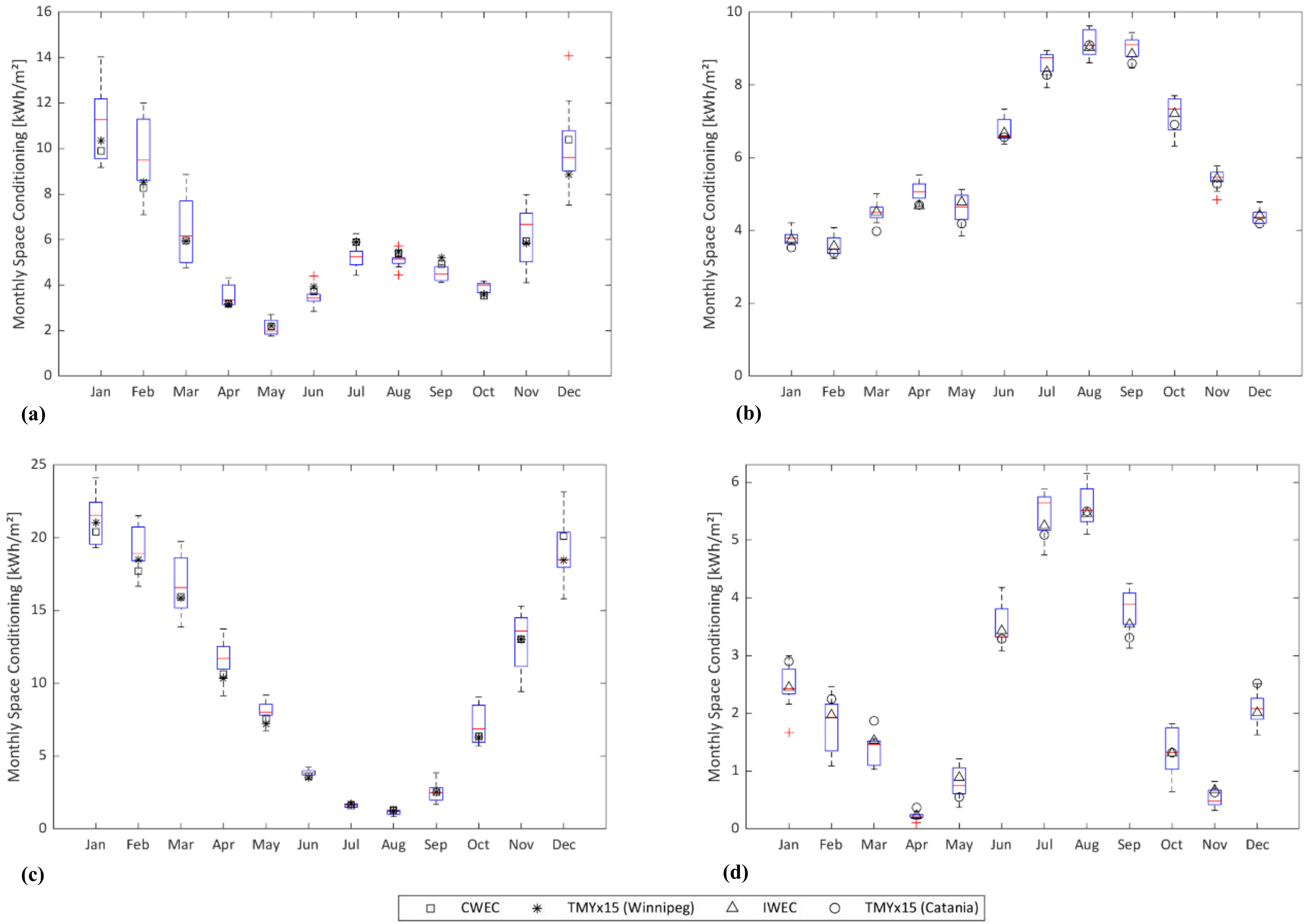


Figure 25: Space conditioning of (a) SPEB Winnipeg, (b) SPEB Catania, (c) House Winnipeg, and (d) House Catania.

4.3.3 Linear regression models and accuracy

Based on the heating and cooling demand results over the ten actual weather years from 2010 to 2019 and the heating and cooling degree days values, we obtained the relationship between these two variables. Figure 26 presents the regression coefficient (R^2) for the residential and university buildings in both climates. Overall, residuals- the distance between the plot points and the regression line- are lower in both climates' heating demand and HDD relationships. Thus, the regression coefficient of heating demand-HDD is considerably more significant than the cooling demand-CDD for both buildings, particularly in Winnipeg, where R^2 for heating is around 0.61 for the house and 0.82 for the SPEB. In contrast, the regression coefficient of 0.02 for cooling of both buildings in Winnipeg indicates a non-existing relationship. Additionally, the R^2 of heating shows the highest values for Catania (0.79 for the house and 0.81 for the SPEB). Furthermore, the correlation between CDD and cooling demand is higher for the SPEB (R^2=0.77) than for the house (0.47) in Catania. The high window-to-wall ratio of SPEB is the likely reason for a higher correlation between the dry-bulb air temperatures and energy consumption than in the single-family house.

Moreover, since heating and cooling degree day values depend only on the outdoor dry-bulb air temperature, the low R^2 values can be explained by the impact of other environmental parameters on buildings' heating and cooling loads, suggesting that CDD and HDD cannot be the only indicators for predicting the potential impact of weather data on these loads. For instance, environmental parameters analysis showed that Winnipeg had high data variability in global horizontal irradiation over the AWYs in July, affecting the cooling load, especially in SPEB with highly glazed surfaces. Also, high variations in relative humidity and internal heat loads impact the latent cooling, which does not correlate well with the dry-bulb air temperature and is not reflected in the regression model.

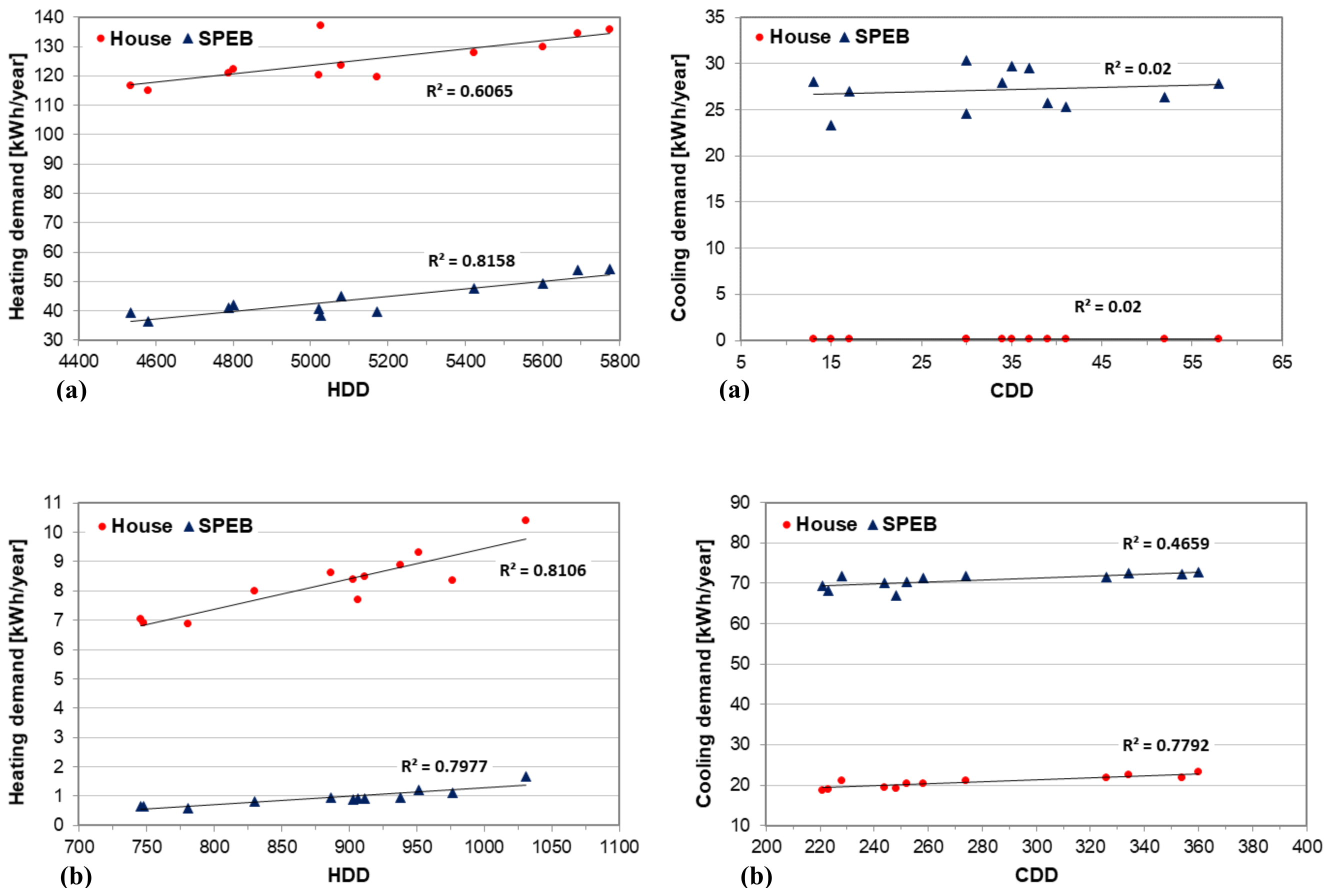


Figure 26: Regression model of the relationship between cooling and heating demand of Winnipeg (a) and Catania (b) and their degree days

Furthermore, Table 8 summarizes the MBE and RSME of both buildings for two climates. MBE results show that both typical weather years for Winnipeg underpredicted heating and overpredicted cooling compared to the ten-year values. In contrast, typical weather years in Catania had the opposite trend, overpredicting the heating and underpredicting the cooling loads. Furthermore, the errors related to heating in Winnipeg and cooling in Catania are higher than those of cooling in Winnipeg and heating in Catania. The tendency of typical weather years of both climates to significantly underpredict dominant space conditioning load is problematic as, on the one hand, it can lead to undersized HVAC systems that fail to provide thermal comfort and indoor air quality to the occupants, and, on the other hand, cause a performance gap between modelled and actual energy consumption.

Table 8: Energy demand discrepancies between TWYs and AWYs for both buildings.

City	TWY	**University building (SPEB)**				**Single-family house**			
		MBE		**RMSE**		**MBE**		**RMSE**	
		Heating	*Cooling*	*Heating*	*Cooling*	*Heating*	*Cooling*	*Heating*	*Cooling*
Winnipeg	CWEC	-5.11	2.89	7.79	3.41	-5.04	0.45	8.4	0.47
	TMY	-6.42	3.78	8.71	4.19	-6.18	0.54	9.13	0.56
Catania	IWEC	0.01	-0.77	0.19	1.6	0.38	-0.54	0.9	1.52
	TMY	0.78	-4.13	0.81	4.36	2.39	-1.71	2.53	2.22

5 Conclusions and Recommendations

Building performance simulation (BPS) has the potential to provide valuable design information by indicating design solution directions. A significant challenge in simulation tools is determining how to deal with difficulties caused by a wide range of parameters and the complexity of factors such as nonlinearity, discreteness, and uncertainty (Hopfe & Hensen, 2011). This research attempted to identify the performance gap caused by weather data as one of the scenario-based uncertainties in building energy simulations. Also, the results of this research showed promising potential to bridge the performance gap caused by unsuitable weather data by analyzing and investigating the impact of widely used typical weather years and comparing them with actual weather years on the predictions of energy simulations. The main conclusions and findings from the studies are as follows:

- To explore and explain differences in energy predictions, we analyzed variations in four main weather parameters, HDD and CDD. For the first study, the annual variation between outdoor air temperature, relative humidity, and global horizontal irradiance was relatively low between the TWY and five AWY for Winnipeg. For example, the percent difference between the mean values of these three environmental parameters ranged from 0.48% for the relative humidity to 4.31% for the dry-bulb air temperature. In contrast, TWY had approximately 70% lower annual average wind speed than AWY over the five actual weather years. This range slightly changed for the ten years of AWYs, ranging from 0.38% for the GHI to 4.05% for the dry-bulb air temperature. Also, the analysis of weather parameters for both locations over the ten years showed that Winnipeg experienced, on average, 24% less solar radiation than Catania but had higher peaks in cold months of the year. The percent difference between the average global horizontal irradiance over the ten years of each climate with their TWYs was between 0.38% and 2.74%. This range varied from 1.35% to 4% for dry-bulb air temperature and from 1.18% to 5.95% for relative humidity. Also, for the TMY weather data of Catania, the wind speed was almost 45% higher than the annual average for the ten years.

- The findings show significantly higher variation in cooling than heating energy predictions between the actual and typical weather years for the first study conducted for the residential building with controlled setpoints under the Winnipeg climate. Thus, CWEC and TMY predicted around 3% lower heating energy demand than the average of five AWYs. On the other hand, two typical years calculated around 36% higher cooling energy demand than the AWYs' average. The discrepancy in the cooling predictions is due to the significantly lower wind velocities of TWY than AWY, which resulted in lower heat dissipation during the summer months. The second study results for two buildings exposed to cold and warm climates show significantly higher variations in cooling than heating load predictions in the heating-dominant climate (Winnipeg) and considerably higher variations in heating load predictions in the cooling-dominant climate (Catania) between the actual and typical weather years. Thus the CWEC and TMY underestimated the heating loads predictions for both buildings under the Winnipeg climate, ranging from 2.7% to 11.3%. These two typical weather years overestimated the cooling loads between 10.5% and 82.4%. In Catania, however, typical representative years, namely IWEC and TMY, underpredicted the cooling demands between 1.8% and 8.7% while overestimating the heating demand predictions from 2.8% to 82.4%. The findings also indicated that CWEC and IWEC typical years are slightly better at predicting buildings' average long-term energy use than the TMY-generated weather years.

- Moreover, the results suggest that relying only on HDD and CDD to predict heating and cooling energy demand is inappropriate. For example, even though HDD and CDD of TMY are closer to the median of the five-year actual weather data than CWEC, the year-by-year analysis showed a more significant discrepancy between heating and cooling predictions of TMY and AWY compared to the CWEC in the first study. The difference was particularly notable for the projections of the cooling energy demand, as the heating prediction of TWYs for the single-family house in Winnipeg was only 2% below the median of AWYs. However, TWYs overestimated the house's cooling load based on the 23 °C cooling setpoint by 35%. These results are not surprising considering that the cooling energy demand calculations are inherently more complicated as they involve solving unsteady equations with unsteady boundary conditions and internal heat sources.
- Typical weather years cannot adequately consider the year-by-year variation in the energy performance of the buildings due to the shifting in climate patterns. The typical years of both climates tend to overpredict or underpredict the peak loads of both buildings. For instance, in the first study in chapter 3, the CWEC and TMY underestimated the heating load and cooling load by 3% and 1%, respectively. Also, in the second study in chapter 4, The heating peak loads of both buildings predicted using the TWYs for Winnipeg are below the ten-year median ranging from 3% to 8.9%. In comparison, heating peak loads of the buildings under the Catania climate are overestimated between 0.7% and 4.25%. These outcomes also suggest that simulation results using AWYs for sizing the technical systems

are more reliable than TWYs in the absence of extreme weather files, such as DSY, XMYor UMY.

- This study provides additional support that a typical single year could not accurately reflect the energy performance of the buildings. It indicates that weather files may have different impacts depending on the type of the simulated building. For example, in SPEB, which is a lightweight building with a highly glazed façade, solar irradiation highly affects the energy use, especially the cooling loads. Hence, the solar irradiation weighting assigned to the TWY is deterministic in the final predictions of building energy demands. Similarly, the residential building with basic envelope features and a much lower window to wall ratio than the SPEB is highly affected by outdoor air temperature and wind speed.

The findings of this research showed that using both actual weather years and typical weather years in building energy simulation should be necessary to estimate the sizing of heating, cooling and ventilation equipment and annual energy demand. Consequently, the building's energy demand prediction should be a range of values derived from running the model using multi-year weather data, which can also indicate the adaptability and robustness of the building under the recent climate change.

Furthermore, To the best of the authors' knowledge, this is the first study to compare the impact of typical single-year and multi-year-by-year weather datasets on the building energy performance under two distinct climates with an extreme need for heating and cooling. Consequently, the conclusions could be of interest to a vast audience working in the field of building performance simulation.

5.1 Recommendations for Future Research

The future work will investigate the implications of different typical and extreme weather files on energy predictions as they are generated through different procedures and their weather parameters have different weightings, which can affect the simulations depending on the type of the modeled building. Moreover, Future results should investigate the impacts of the data recorded from a weather station on typical buildings at different distances from the weather station. As a result, the impact of changes in microclimatic conditions (e.g., wind speed) can be evaluated since relocating a potential structure Crossing a weather file boundary by 100m on a site could result in significant changes in predicted performance. Also, other studies should evaluate the effect of synthetic weather data using weather generators that produce a long-term series of weather parameters comparable to existing historical records by computer algorithms. Hence, the results can be compared to the AWYs to identify uncertainties.

The results of this study were only based on the conventionally constructed Canadian single-family house and a LEED-certified lightweight 4-story building with a curtain-wall façade system based on Canadian building codes. Further studies need to include different types of buildings with different requirements for code compliance, such as mid-rise and high-rise residential buildings, and more complex commercial and institutional buildings with advanced envelope characteristics, including enclosures with high thermal mass. Further studies should include weather datasets from other climates with specific weather conditions, such as semi-arid, humid subtropical, tropical, oceanic, and desert climates. Future research should also investigate the effects of weather files on heating and cooling energy predictions generated using other building performance simulation tools such as TRNSYS, DeST, and IES. The results from different BPS tools will help identify the impact of boundary condition parameters on the energy predictions of these tools. They may use different calculation methods for parameters like convection coefficient, which can considerably affect the cooling and heating loads.

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Appendix A: Environmental Parameters

The variation range (difference between the minimum and maximum) for the annual average dry-bulb temperature varied from 61.8 to 69.9 °C in Winnipeg. However, the range is much lower in Catania, from 32.2 to 41.13 °C (see Tables 9 and 10). Also, Winnipeg's annual average wind speed is much higher than Catania over the AWYs. Nevertheless, the TWYs of Winnipeg are approximately 70% lower than the average wind speed over the ten AWYs. Also, in Catania, the average wind speed of TMY is 40% higher than the average wind speed of actual weather years. Although Catania experienced higher annual average global horizontal irradiance, Winnipeg had higher peaks.

Table 9: Annual Minimum, mean, and maximum values of four environmental parameters of Winnipeg

	DB air temperature			**Relative humidity**			**Wind speed**			**Global Horizontal Irradiance (GHI)**		
	Min	**Mean**	**Max**	**Min**	**Mean**	**Max**	**Min**	**Mean**	**Max**	**Min**	**Mean**	**Max**
Unit		°C			%			m/s			Wh/m²	
2010	-29.8	6.4	34.5	13.0	70.5	100.0	0.0	9.4	68.0	154	3442	8460
2011	-29.8	5.0	35.9	15.3	68.0	100.0	0.0	8.1	52.4	334	3710	8669
2012	-27.8	5.8	34.4	13.0	66.3	100.0	0.0	8.3	55.3	275	3565	8775
2013	-31.7	3.1	33.3	13.0	66.8	95.0	0.0	8.0	25.3	278	3720	8743
2014	-32.0	2.8	31.9	15.4	68.2	97.0	0.0	7.7	24.0	228	3507	8671
2015	-29.5	5.7	33.3	13.0	67.3	97.0	0.0	7.8	42.5	225	3730	8643
2016	-27.8	6.1	34.3	10.4	68.8	97.6	0.0	6.7	22.5	201	3683	8842
2017	-31.1	4.9	33.5	13.0	65.5	97.0	0.0	6.9	25.0	116	3706	8643
2018	-28.3	4.2	36.4	11.0	64.7	96.0	0.0	6.5	25.0	273	3667	8542
2019	-34.7	3.4	35.3	15.6	66.1	99.0	0.0	6.9	25.0	309	3702	8870
CWEC	-28.5	4.7	33.3	12.4	68.4	99.0	0.0	2.1	9.4	291	3575	8456
TMY	-29.0	4.9	33.3	13.0	66.1	100.0	0.0	2.1	11.7	206	3657	8519

Table 10: Annual Minimum, mean, and maximum values of four environmental parameters of Catania

	DB air temperature			Relative humidity			Wind speed			GHI		
	Min	**Mean**	**Max**	**Min**	**Mean**	**Max**	**Min**	**Mean**	**Max**	**Min**	**Mean**	**Max**
Unit		°C			%			m/s			Wh/m²	
2010	2.0	18.1	36.2	14.8	70.5	99.6	0.0	2.1	9.5	314	4562	8193
2011	0.8	17.9	35.0	18.6	67.7	96.0	0.2	2.4	8.7	180	4540	7849
2012	0.4	18.4	39.4	10.0	63.1	95.0	0.2	2.5	12.1	200	4811	8134
2013	2.1	18.2	35.5	17.1	63.9	91.0	0.2	2.5	9.1	179	4658	8253
2014	2.3	18.5	38.2	9.0	63.6	91.0	0.2	2.4	11.8	433	4804	8562
2015	1.6	18.3	39.4	13.4	65.7	98.0	0.2	2.3	8.7	289	4812	8479
2016	2.2	18.6	34.4	12.0	69.8	100.0	0.2	2.5	9.8	276	4813	8494
2017	1.1	18.1	39.8	8.4	65.2	100.0	0.3	2.4	8.1	240	5144	8445
2018	2.5	18.7	39.8	9.4	66.5	100.0	0.2	2.5	10.3	425	4703	8419
2019	1.3	18.4	41.5	9.0	63.8	100.0	0.3	2.7	9.6	200	4910	8519
CWEC	-0.2	18.1	40.9	12.0	66.8	98.0	0.0	2.3	12.1	180	4738	8094
TMY	0.5	17.8	37.6	4.6	69.9	100.0	0.0	3.5	13.9	1176	4906	8110

Table 11 shows monthly variation between the minimum, average, and maximum of four main environmental parameters for AWYs of Winnipeg. Also, the same information for Winnipeg's CWEC and TMY weather data can be seen in Tables 12 and 13, respectively. It is evident that CWEC and TMY discarded the extreme values, and the monthly range between the maximum and minimum is narrower than the range in AWYs. Similarly, the standard deviation of monthly environmental parameters for IWEC and TMY of Catania is lower than AWYs; hence the maximum and minimum values are closer to the mean.

Table 11: Monthly Minimum, mean, and maximum values of four environmental parameters for **AWYs** of Winnipeg

	DB air temperature			Relative humidity			Wind speed			GHI		
	Min	Mean	Max	Min	Mean	Max	Min	Mean	Max	Min	Mean	Max
Unit		°C			%			m/s			Wh/m²	
Jan	-34.65	-13.62	7.26	47	75	97	0.0	7.9	42.5	116	1170.7	2399
Feb	-30.73	-12.81	7.09	37	72	96	0.0	7.4	25.5	352	2066.3	3904
Mar	-31.99	-3.83	22.86	18	70	100	0.0	8.4	52.4	735	3606.1	5816
Apr	-17.73	4.61	25.74	12	56	96	0.0	8.1	23.5	478	5110.2	7604
May	-6.04	13.02	34.31	10	56	96	0.0	7.8	29.1	1109	5650.9	8733
Jun	4.10	18.70	35.28	16	62	96	0.0	6.5	23.8	1285	6096.3	8870
Jul	9.20	21.69	33.95	22	62	95	0.0	6.5	22.8	1522	6470.3	8669
Aug	7.14	20.33	36.40	17	63	96	0.0	6.1	20.0	1126	5320.0	7832
Sep	-1.82	14.87	33.21	18	67	100	0.0	7.8	36.3	309	3612.2	6117
Oct	-8.29	6.77	30.89	13	70	100	0.0	8.3	68.0	95	2146.6	4263
Nov	-23.76	-2.69	18.82	29	76	97	0.0	8.4	45.1	22	1249.5	2518
Dec	-31.74	-11.24	6.58	38	78	100	0.0	8.3	55.3	228	1015.6	1669

Table 12: Monthly Minimum, mean, and maximum values of four environmental parameters for **CWEC** of Winnipeg

	DB air temperature			Relative humidity			Wind speed			GHI		
	Min	Mean	Max	Min	Mean	Max	Min	Mean	Max	Min	Mean	Max
Unit		°C			%			m/s			Wh/m²	
Jan	-28.45	-12.52	6.28	56	77	94	0.23	2.74	9.36	630	1273	1850
Feb	-27.50	-12.49	1.90	40	75	99	0.00	2.10	5.91	1040	2327	3517
Mar	-22.95	-4.52	13.21	32	65	96	0.11	2.05	5.49	2098	3578	5323
Apr	-8.90	5.48	22.38	14	64	95	0.00	2.02	5.49	1830	4905	7180
May	2.84	12.95	28.93	12	62	95	0.00	2.38	6.23	2407	5419	8456
Jun	7.49	18.37	33.05	24	63	94	0.23	1.85	5.80	2355	5858	8314
Jul	13.84	21.91	32.49	30	65	94	0.00	1.81	5.60	2071	6205	8212
Aug	9.34	19.93	33.30	29	68	96	0.00	1.81	5.27	1605	5195	7069
Sep	4.70	14.85	33.21	19	66	95	0.00	1.94	5.19	1195	3642	5746
Oct	-2.34	7.52	18.40	29	69	97	0.00	2.16	6.29	687	2196	4101
Nov	-18.14	-3.25	11.54	39	72	96	0.00	2.18	5.49	314	1225	2156
Dec	-27.79	-13.43	-0.91	50	77	92	0.00	2.18	6.89	291	1000	1318

Table 13: Monthly Minimum, mean, and maximum values of four environmental parameters for **TMY** of Winnipeg

	DB air temperature			Relative humidity			Wind speed			GHI		
	Min	Mean	Max	Min	Mean	Max	Min	Mean	Max	Min	Mean	Max
Unit		°C			%			m/s			Wh/m²	
Jan	-28.96	-12.74	4.33	48	71	97	0.31	3.46	11.68	441	1121	2333
Feb	-28.00	-12.51	2.00	41	75	100	0.00	2.03	5.91	375	1960	3883
Mar	-22.95	-4.53	13.21	34	65	98	0.00	2.04	5.48	1053	3660	5505
Apr	-5.41	5.80	20.91	13	55	95	0.00	1.99	6.20	2307	5141	7558
May	1.45	12.60	23.82	14	52	90	0.00	2.10	5.29	2645	5894	8366
Jun	8.29	18.29	30.73	26	63	94	0.08	1.81	5.62	2230	6107	8519
Jul	12.16	21.46	31.79	26	63	94	0.00	1.67	4.29	2931	6525	8398
Aug	9.30	19.86	33.30	30	68	98	0.00	1.78	5.29	1606	5184	7507
Sep	3.00	14.60	30.63	23	65	98	0.00	1.92	5.91	1034	3893	5931
Oct	-2.00	7.72	18.00	31	70	100	0.00	2.09	6.23	206	2192	4118
Nov	-18.00	-3.21	12.00	37	72	100	0.00	2.12	5.41	318	1181	1987
Dec	-28.30	-9.25	4.02	54	76	95	0.00	1.95	5.89	490	917	1113

Table 14: Monthly Minimum, mean, and maximum values of four environmental parameters for **AWYs** of Catania

	DB air temperature			Relative humidity			Wind speed			GHI		
	Min	Mean	Max	Min	Mean	Max	Min	Mean	Max	Min	Mean	Max
Unit		°C			%			m/s			Wh/m²	
Jan	0.4	10.8	22.8	21	71	100	0.0	2.5	10.3	180	2454	3809
Feb	1.4	11.3	24.3	25	70	100	0.0	2.6	10.1	237	3132	5102
Mar	0.8	13.2	26.7	20	69	100	0.0	2.7	12.1	179	4476	6842
Apr	5.1	15.7	32.4	12	69	100	0.0	2.6	9.5	700	5808	8193
May	7.9	18.9	33.2	13	64	100	0.0	2.6	9.5	1309	6611	8368
Jun	12.2	23.3	40.2	9	60	96	0.0	2.4	8.1	2266	7291	8562
Jul	16.5	26.5	41.5	8	56	96	0.0	2.3	7.7	2509	7443	8401
Aug	18.5	26.8	39.4	10	58	93	0.0	2.2	6.4	2806	6583	8050
Sep	13.7	24.1	39.4	13	63	98	0.0	2.3	8.3	655	5058	6878
Oct	9.8	20.4	31.4	20	70	100	0.0	2.2	8.8	200	3603	5680
Nov	3.6	16.1	28.3	24	74	100	0.0	2.3	11.8	240	2554	4120
Dec	1.4	12.1	26.7	20	70	100	0.0	2.5	9.8	220	2187	3189

Table 15: Monthly Minimum, mean, and maximum values of four environmental parameters for **IWEC** of Catania

	DB air temperature			Relative humidity			Wind speed			GHI		
	Min	Mean	Max	Min	Mean	Max	Min	Mean	Max	Min	Mean	Max
Unit		°C			%			m/s			Wh/m²	
Jan	3.4	10.6	20.4	37	78	96	0.2	2.4	7.3	180	2464	3113
Feb	-0.2	10.4	20.6	23	67	91	0.0	2.4	7.2	517	3268	4917
Mar	4.1	12.7	22.3	22	68	95	0.1	2.7	12.1	515	4592	6164
Apr	7.3	15.2	22.6	29	70	98	0.0	2.8	7.1	700	5418	7888
May	10.6	19.3	32.1	16	60	91	0.0	2.0	6.3	3211	6539	8089
Jun	13.8	22.8	32.3	24	63	97	0.2	1.9	5.7	4842	7251	8094
Jul	18.3	26.3	40.9	12	53	91	0.0	2.0	5.8	6518	7453	8052
Aug	18.0	26.5	40.9	14	61	95	0.0	1.9	4.6	5300	6510	7145
Sep	14.6	23.8	31.1	24	64	89	0.0	2.2	6.5	2462	4914	6157
Oct	12.7	20.6	30.9	29	73	98	0.0	2.2	6.1	686	3525	4959
Nov	7.3	15.7	25.1	32	72	92	0.0	2.6	6.4	1159	2772	4120
Dec	4.2	12.3	21.0	29	72	94	0.0	2.1	7.2	264	2058	2992

Table 16: Monthly Minimum, mean, and maximum values of four environmental parameters for **TMY** of Catania

	DB air temperature			Relative humidity			Wind speed			GHI		
	Min	Mean	Max	Min	Mean	Max	Min	Mean	Max	Min	Mean	Max
Unit		°C			%			m/s			Wh/m²	
Jan	1.9	10.2	18.0	34	76	94	0.3	3.6	11.0	1176	2394	3230
Feb	1.8	10.2	17.8	41	74	97	0.0	2.9	11.6	1769	3247	4547
Mar	1.2	12.4	23.0	24	71	94	0.0	4.6	12.2	1661	4517	6260
Apr	6.0	15.3	24.0	37	73	100	0.0	3.2	12.9	2388	5728	7170
May	8.4	18.5	30.7	29	67	94	0.0	4.1	11.9	3207	6911	7904
Jun	14.0	23.3	32.3	29	61	93	0.1	3.4	9.5	5599	7532	8110
Jul	16.1	26.1	36.4	29	60	88	0.0	3.5	11.2	5475	7575	8015
Aug	18.0	26.6	37.6	29	66	100	0.0	3.2	9.0	5531	6824	7480
Sep	12.8	23.4	37.6	16	66	94	0.0	3.6	11.3	3833	5425	6462
Oct	9.0	20.1	35.3	30	76	95	0.0	2.8	10.4	1637	3670	5082
Nov	4.4	15.3	23.6	5	81	100	0.0	2.9	10.4	1824	2705	3337
Dec	0.5	11.2	20.0	34	68	93	0.0	4.3	13.9	1250	2242	2730

Figures 27 and 28 show the annual average dry-bulb air temperature and wind speed of Winnipeg and Catania, respectively. These figures show that the annual average dry-bulb air temperature variation is more significant in Winnipeg than in Catania. The difference between the hottest year and the coldest year in Catania is below 1 °C, while for Winnipeg, this difference is 3.6 °C. Also, both climates' annual average wind speed did not vary significantly over the ten AWYs—however, the average wind speed of TWYs for Winnipeg is considerably lower than AWYs. The average wind speed of TMY for Catania is also significantly higher than IWEC and the ten years of observation.

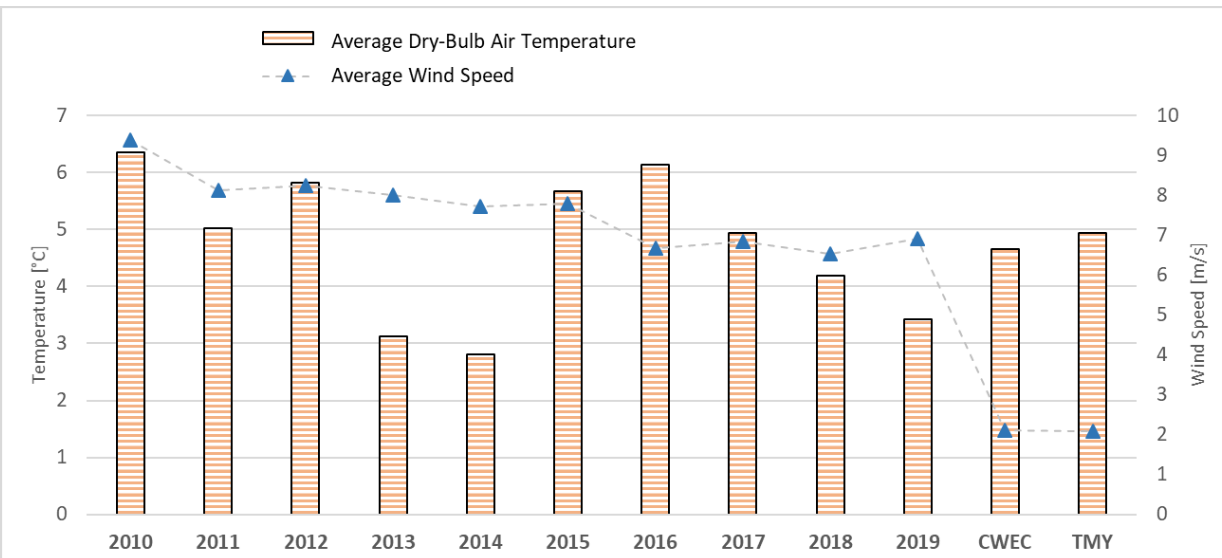

Figure 27:Year-by-Year Variation in Average DB Air Temperature and Wind Speed in Winnipeg

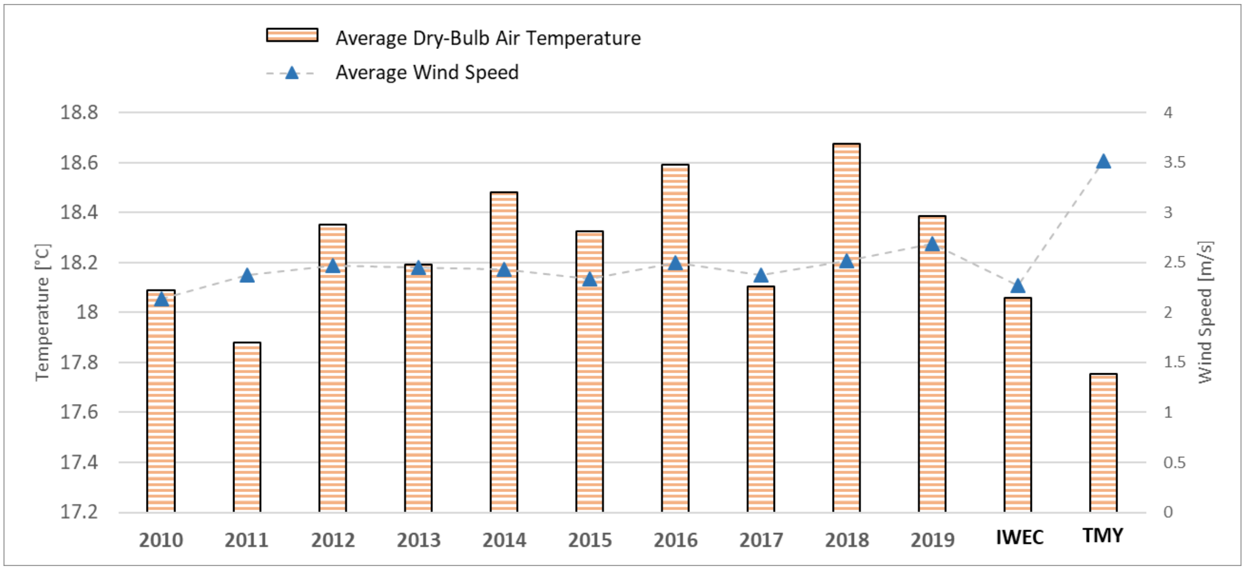

Figure 28: Year-by-Year Variation in Average DB Air Temperature and Wind Speed in Catania

Figure 29 shows the monthly variation in average dry-bulb air temperature and wind speed for TWY of Winnipeg. According to the figure, the difference between the average wind speed of CWEC and TMY is relatively the same in each month except in January. In Catania, however, the high variation in average wind speed between IWEC and TMY occurred every month (see Figure 30).

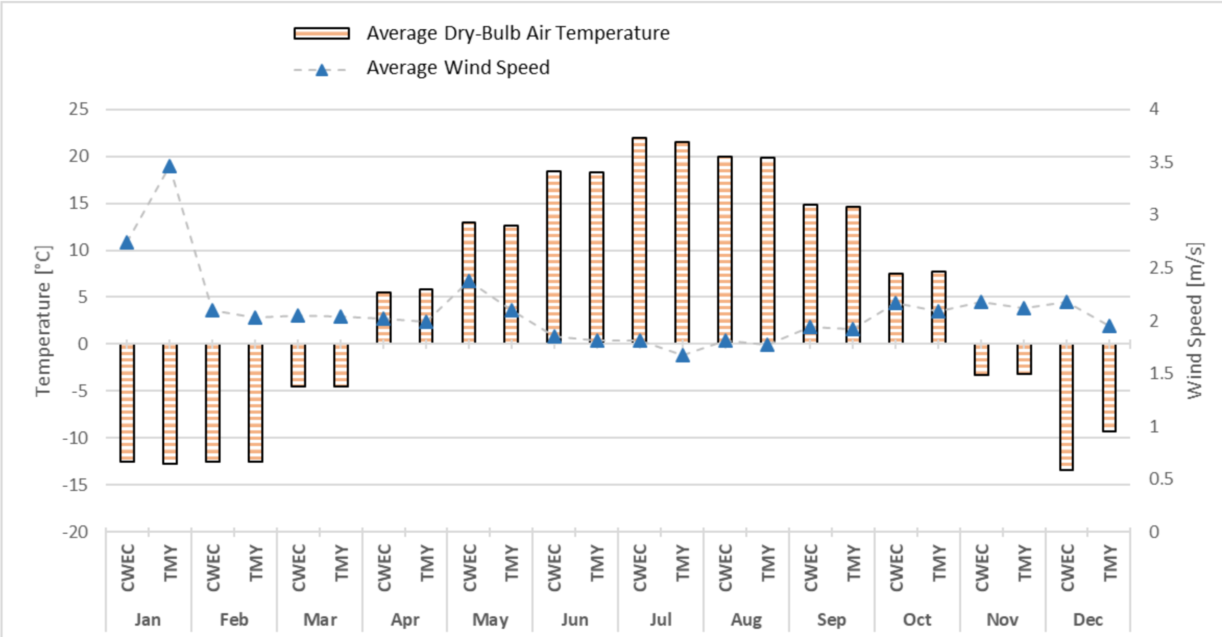

Figure 29: Monthly average wind speed and temperature variation of TWYs for Winnipeg

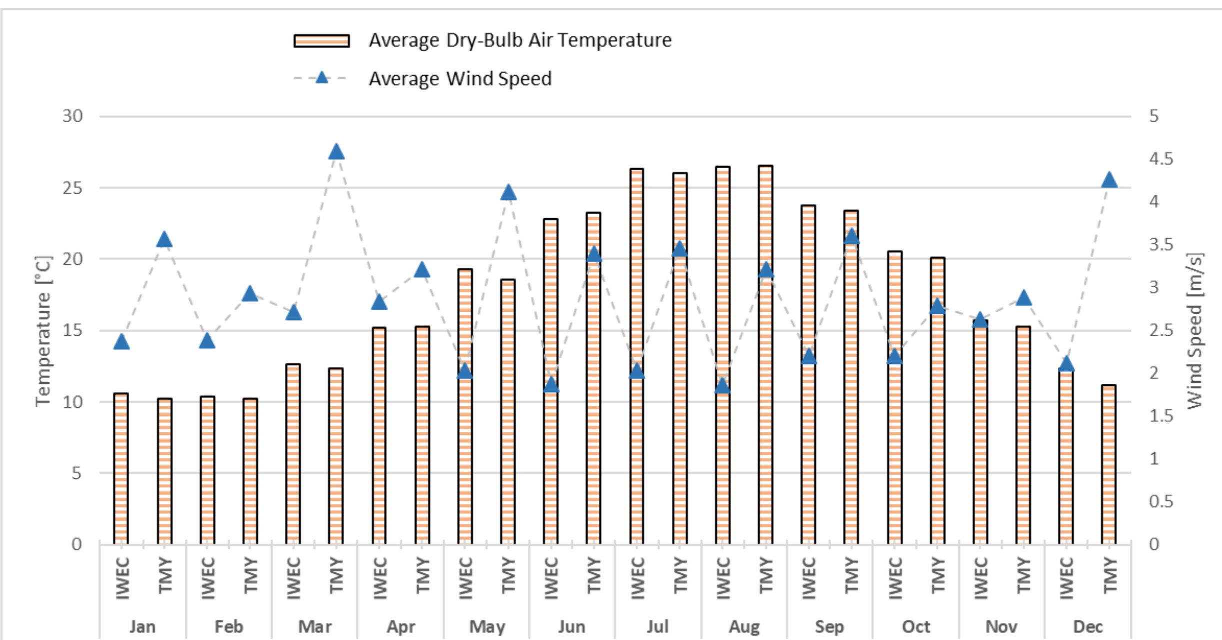

Figure 30: Monthly average wind speed and temperature variation of TWYs for Catania

Appendix B: Heating and Cooling Demand of Single-Family House and SPEB in Winnipeg and Catania

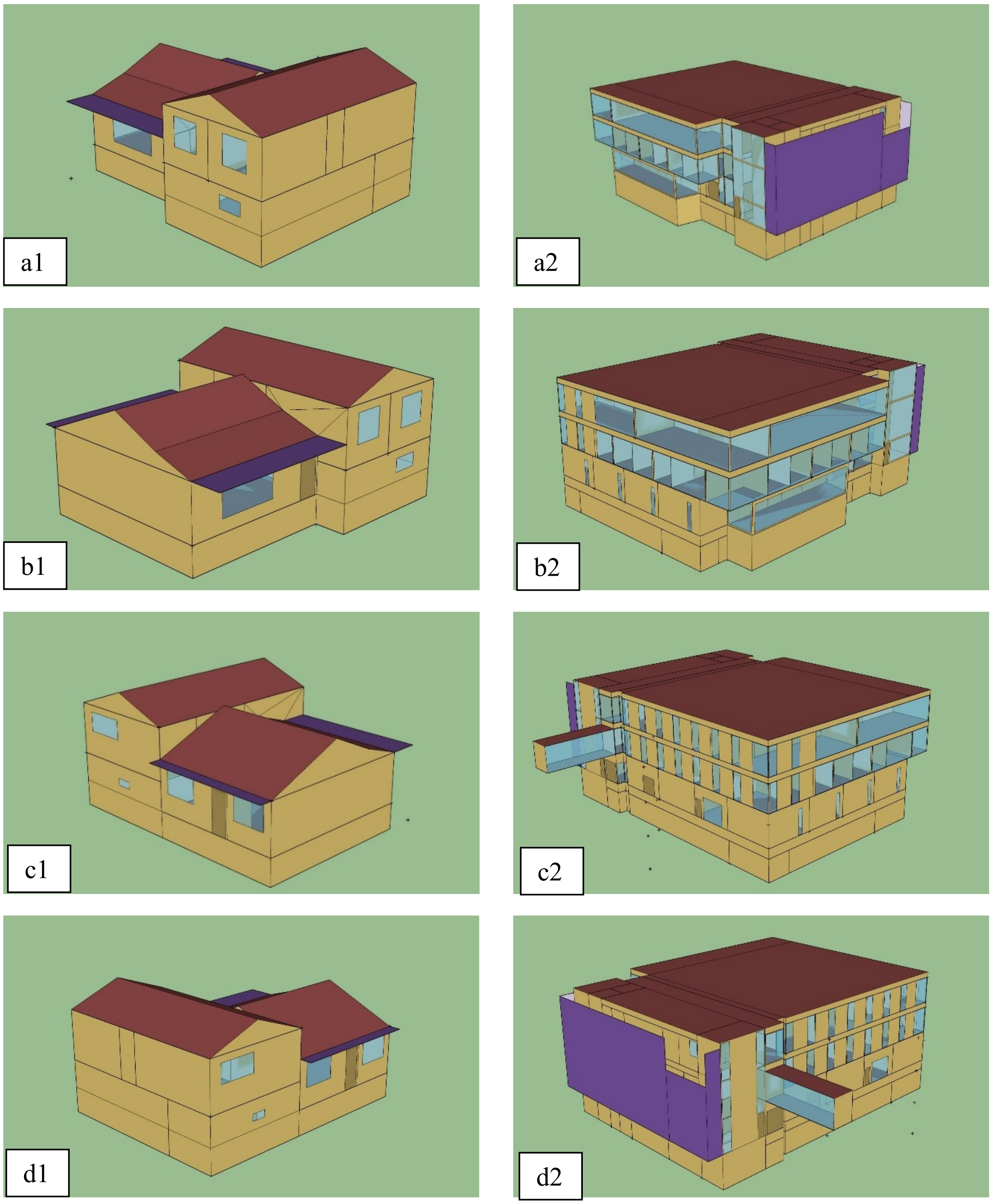

Figure 31: modeled house (1) and the SPEB (2) in Sketchup/OpenStudio. (a) Southeast, (b) Southwest, (c) Northwest, (d) Northeast. Note: adjacent shading surfaces are excluded in the figures.

Annual Variation in Heating and Cooling Demands

Figure 32 shows year-to-year variations in heating and cooling that needs to be predicted by a simulation of actual weather years with forecasts from two different versions of typical weather years of both climates.

Comparing both buildings, the highest need for heating occurred in 2014 in Winnipeg, which was approximately 54.3 kWh/m² for the house and 135.7 kWh/m² for the SPEB and then followed by the year 2013, which these values experienced a decrease of only 1 kWh/m². Furthermore, from 2016 to 2019, an increasing pattern for heating load in Winnipeg can be seen. For Catania AWYs, the house's heating load ranges between 0.65 kWh/m² and 1.22 kWh/m², while this range varies from 6.87 kWh/m² to 9.3 kWh/m² for the SPEB. For Winnipeg and Catania weather data, both buildings had the highest cooling demand in 2010 and 2019. Figure 32 also indicates that the need for space heating and cooling calculated by TWYs are comparable to other actual weather years except for the cooling loads calculated by Winnipeg typical years. Figure 12 compares single-year simulations with multi-year simulations to demonstrate the fluctuation of year-by-year heating and cooling demands. The percent difference is calculated using the mean of all AWYs from 2010 to 2019. The variations in the energy consumption for space heating are closer to the mean in the residential building. The variation of the heating load of the residential building in Winnipeg ranges between -7.6% in 2016 and 8.91% in 2014, and as for Catania, this range is between -14.09 in 2014 and 16.26% in 2012. figure 33-b shows that heating load variations are much more pronounced in the university building, varying from -19% to 20% in Winnipeg and from -33.8% to 38.4% in Catania.

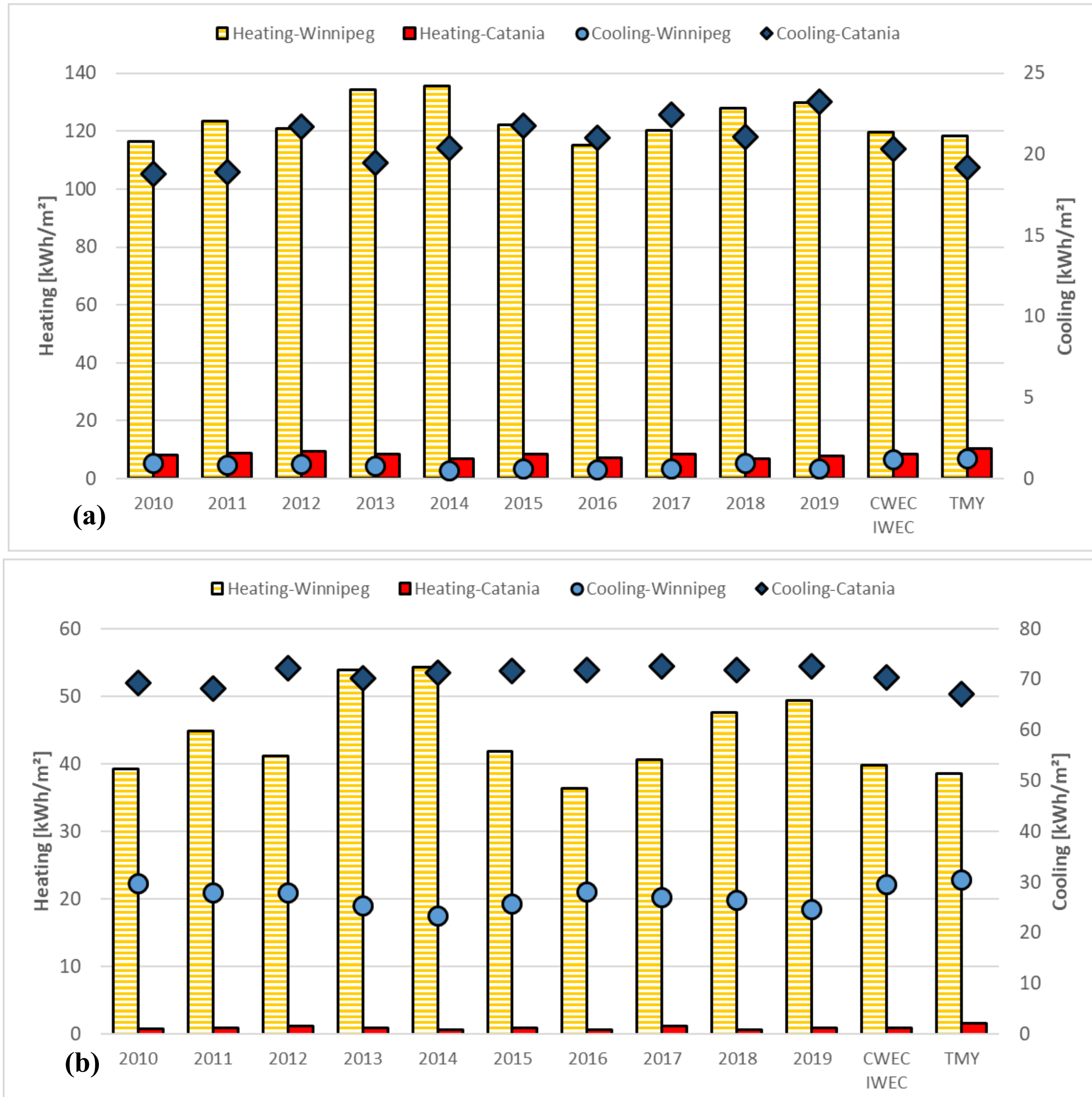

Figure 32: Year-by-year heating and cooling loads for ten actual and two typical weather years of the house (a) and the SPEB (b)

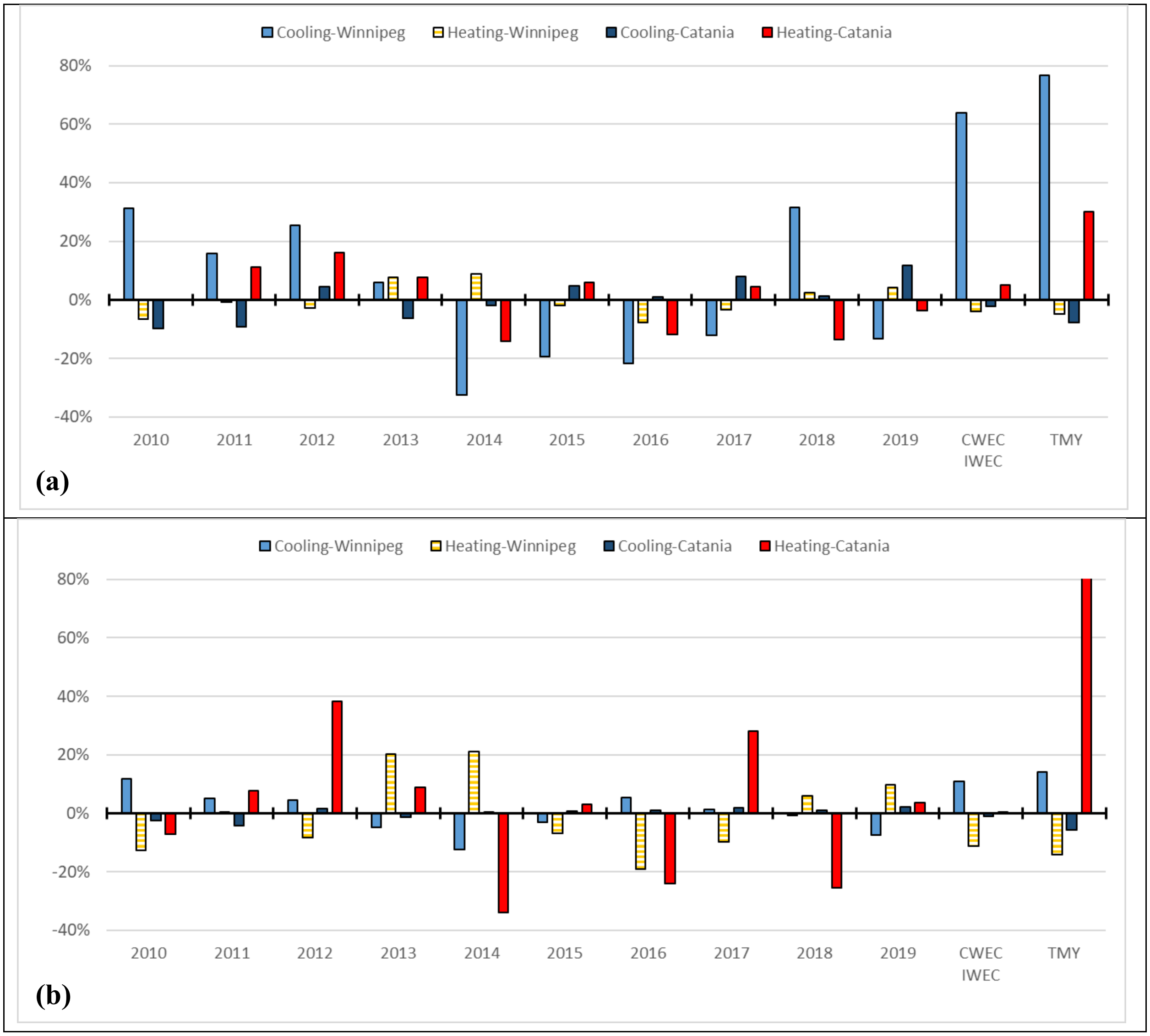

Figure 33: Year-by-year heating and cooling loads for ten actual and two typical weather years of the house (a) and the SPEB (b)

Monthly Variation in Heating and Cooling Demand

As shown in figure 34, the house has a higher demand for space heating under Winnipeg climatic conditions, and the heating season is longer than in Catania. The typical weather values for the house in Winnipeg mostly fall between the interquartile range and are below the median except for CWEC in December. Also, the difference between TMY and CWEC weather data ranges between 0.04% and 5.29% from January to November; however, this difference reaches 9% in

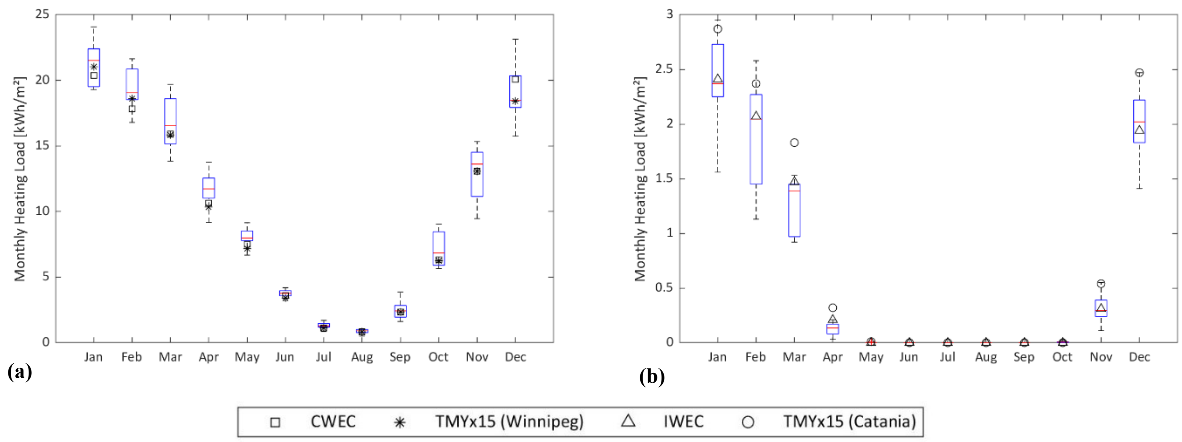

Figure 34: Monthly variation in heating demand for the residential building in Winnipeg (a) and Catania (b)

December. The reason is the lower average dry-bulb air temperature in December for CWEC weather data (around 30%) than TMY (see Figure 30). By contrast, Catania's TWYs are above the heating distribution median of each month, and this overestimation in heating load is much higher by using TMY as the weather file input for the residential building simulation.

Figure 35 also shows that the TWYs overestimated the cooling load in the residential building under the Winnipeg climate, falling outside the interquartile range. Except for TMY in August, TWYs are outliers between July and September, resulting from very low wind speeds compared to AWYs. The TWYs for Catania are below the median and follow a similar monthly pattern, with IWEC closer to the monthly heating distribution median.

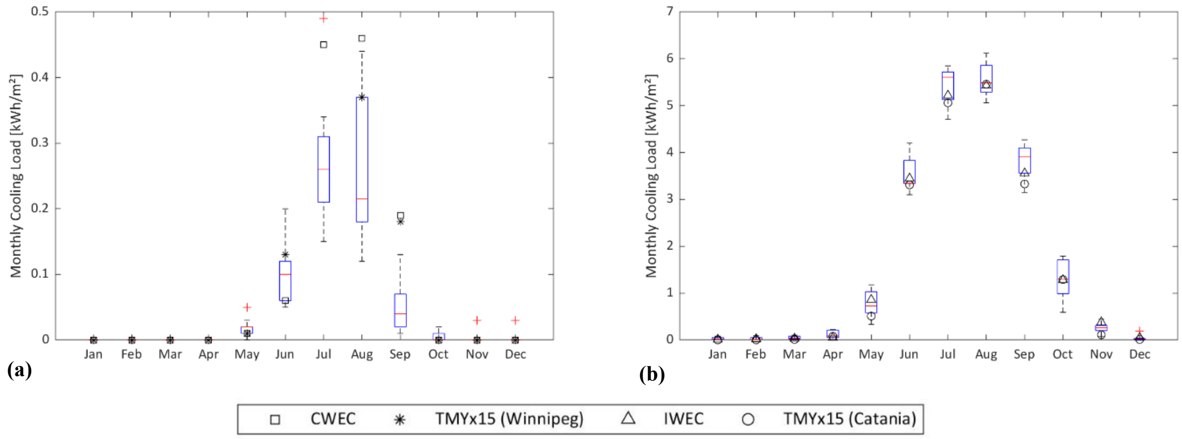

Figure 35: Monthly variation in cooling demand for the residential building in Winnipeg (a) and Catania (b)

The SPEB also has the same pattern as the residential building in both climates, as illustrated in figure 36. However, the heating load distribution boxplots are much more extensive in the SPEB.

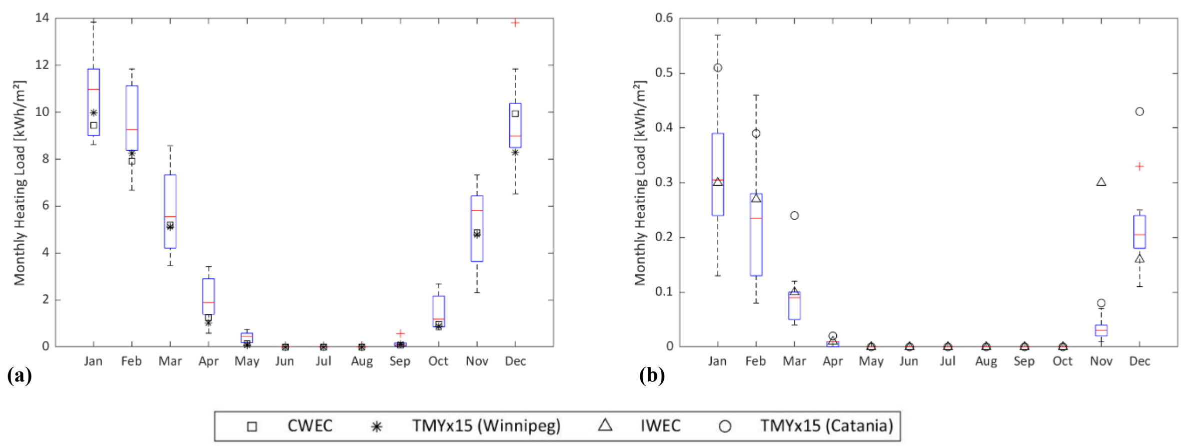

Figure 36: Monthly variation in heating demand for SPEB in Winnipeg (a) and Catania (b)

The Cooling demand is much higher than the residential building, especially in Catania, where the SPEB also needs cooling during the colder months (see Figure 37). The higher need for space cooling in SPEB can be justified by the high impacts of internal heat loads and solar radiation that increase the cooling demand of the highly glazed university building. TWYs of Winnipeg overestimated the cooling load and fell outside the IQR in the cooling season. The gap between the two typical years was also below 5.5% during the summer. On the other hand, the two typical weather years underestimated the cooling load for most months, with TMY being outside the IQR from November until August. The gap between the TWYs is also much more sensible in April and March. The analysis of environmental parameters showed that this gap between IWEC and TMY can be explained by the higher average wind speed of TMY in these months, which increased convective heat losses and thus reduce predictions for the cooling load of TMY.

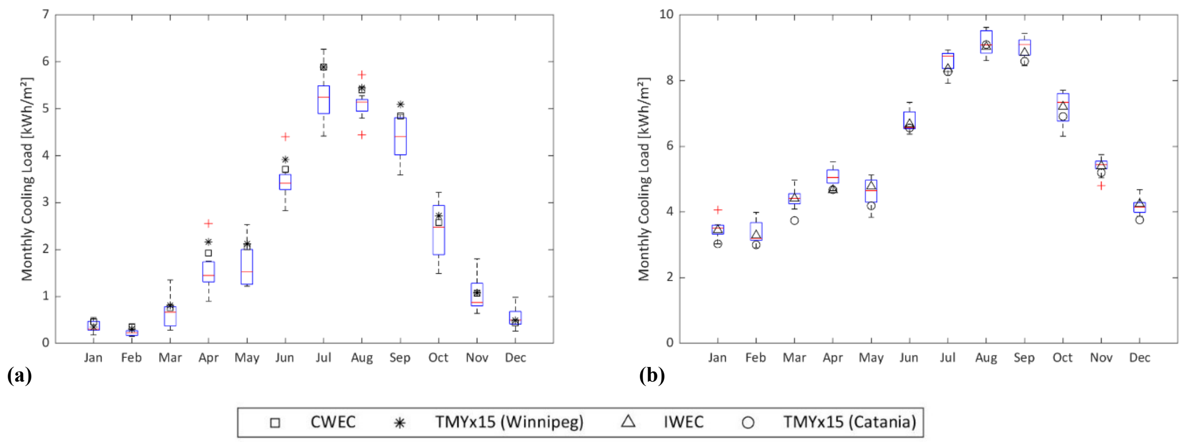

Figure 37: Monthly variation in cooling demand for SPEB in Winnipeg (a) and Catania (b)