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Review

An Overview of Climate Change and Building Energy: Performance, Responses and Uncertainties

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Abstract: It is becoming increasingly crucial to develop methods and strategies to assess building performance under the changing climate and to yield a more sustainable and resilient design. However, the outputs of climate models have a coarse spatial and temporal resolution and cannot be used directly in building energy simulation tools. This paper reviews methods to develop fine spatial and temporal weather files that incorporate climate emissions scenarios by means of downscaling. An overview of the climate change impact on building energy performance is given, and potential adaptation and mitigation factors in response to the changing climate in the building sector are presented. Also, methods to reflect, propagate, and partition main sources of uncertainties in both weather files and buildings are summarized, and a sample approach to propagate the uncertainties is demonstrated.

Keywords: sustainable & resilient; weather files; responses; uncertainties

1. Introduction

Buildings, through their lifecycle, play an important role in energy consumption and Greenhouse Gas (GHG) emissions [1] both directly (i.e., through its operation [2]) and indirectly (i.e., through the production of building materials [3], construction processes [4,5], transportation [6], rehabilitation, and demolition [7]). While these impacts underscore the importance of applying a dynamic approach [8–10] in life cycle assessments, the primary share of both energy consumption and environmental impacts takes place during a building's operation [2–6,11,12]. The operation phase of a building can be 50–100 years or more, and the performance of a building during this time is not static. For example, the thermal conductivity of construction [13] and insulation materials [14] are directly influenced by outdoor weather conditions, which are not only sensitive to short term changes (i.e., seasonal variability) but also long-term climate dynamics. The focus of this paper is climate change impacts on building operation and performance, which are assessed using building simulation tools. Building simulation tools solve dynamic equations with respect to building thermodynamics and physics and are widely used to assess energy performance. The use of dynamic simulation tools becomes even more complicated with the changing climate, and given the many sources of uncertainties (from both the building and climate), strategies to evaluate their performance under future scenarios are necessary. Yet climate models lack the temporal resolution to be utilized by simulation tools, which require weather files in an hourly format. In this paper, we review methods to generate future hourly weather files from climate change emission scenarios for building simulations. We also highlight key findings in the literature on future building performance as a result of climate change. First, a summary of climate models and methods to generate fine spatial and temporal resolution weather files is presented. Next, predicted impacts on building energy performance using a combination of downscaled weather files and building simulation tools are reviewed. We find there is a gap in the scholarship addressing the combined effect of design condition and weather files on future building performance. Finally, potential adaptation and mitigation factors in response to the changing climate are reviewed as well as methods to reflect, propagate and partition main sources of uncertainties stemming from both buildings and weather files. We close by offering a sample probabilistic approach for propagating uncertainties in building energy performance under future climate conditions.

2. Climate Projections

Increased GHG emissions produced by human activities interact with the climate's balance [15] and has changed climate trends. While the changes may vary by decade, surface temperatures have increased since 1880 (Figure 1).

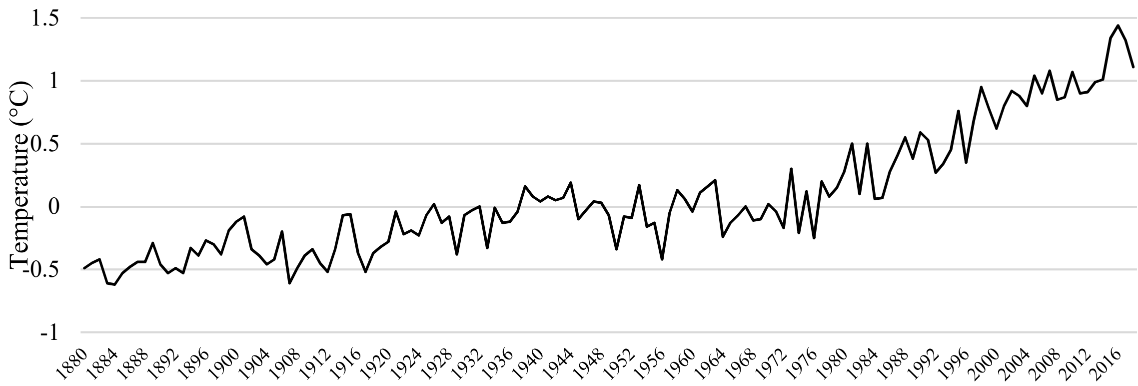

Figure 1. Global land temperature anomalies 1880–2018 [16].

Figure 1 shows the annual surface temperature anomaly, which is the difference between the long-term temperature and the observed temperature and shows an approximately 1 °C increase since 1880 globally. The increasing trend in temperatures is attributed to increased GHG emissions primarily due to the burning of fossil fuels. An approximately 100ppm increase in CO_2 concentration has been measured globally since 1978 [17]. The Intergovernmental Panel on Climate Change (IPCC) developed climate emissions scenarios to enhance our understanding of how the future might look [18]. The IPCC is an intergovernmental body that reviews technical and scientific reports around the world related to climate change. The United Nations Environmental Programme and the World Meteorological Organization (WMO) established the IPCC [19]. The first IPCC scenario was developed in 1990, followed by the Third Assessment Report (TAR), the Fourth Assessment Report (AR4) and the most recent Fifth Assessment Report (AR5), where four different scenarios, called the Representative Concentration Pathways (RCPs), were introduced.

The first step for climate prediction is defining future scenarios. The emissions scenarios are incorporated into General Circulation Models (GCM) and Regional Circulation Models (RCM), which are models used to understand climate behavior and to forecast probable changes [20]. GCMs/RCMs simulate the changes in the climate over time and illustrate how climate components (surface, atmospheric, and oceanic) interact with each other in order to develop an understanding of their variability. Figure 2 shows the trend of different scenarios from the TAR, projected to 2100. They are called projections because future GHG emissions are unknown. The projections present a snapshot of the possibilities that may occur in the future based on current emissions status and assumptions about socioeconomic factors such as population, economic, and technological developments [21].

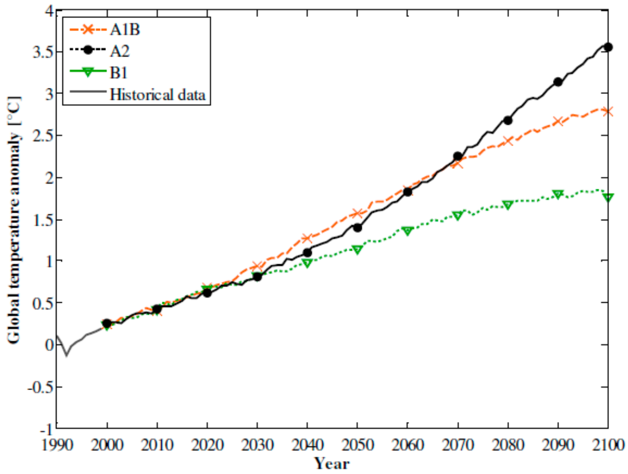

Figure 2. Yearly mean temperatures for different Greenhouse Gas (GHG) emissions scenarios [22].

In Figure 2 the most extreme scenario (A2) projects an approximate 3.5 °C increase, a 2.5 °C for the A1B scenario and the most conservative scenario (B1) shows a 1.5 °C increase in global temperature by the 21st century. Based on the emissions scenarios in Figure 2, it is apparent that the differences between most emission scenarios are not expected to be significant prior to 2040. This is mainly due to the inertia of the climate and the ~100-year lifespan of CO_2 emissions [19]. The North American Regional Climate Change Assessment Program [23] and the IPCC data distribution center [24] provide outputs from different climate models for different locations and time scales using various emission scenarios. However, these data are at best on a 3-hourly temporal resolution (see Appendix A) and have a coarse spatial resolution, obviating their direct application in building simulations. To obtain a fine spatial and temporal resolution, the use of downscaling techniques is required. Downscaling can be done dynamically (using RCMs) or statistically (stochastic methods or morphing). Moazami et al. (2019) provides a detailed description of advantages and disadvantages of dynamic and statistical downscaling methods [25]. The next section reviews different methods used to generate the necessary weather information for building performance analysis using statistical downscaling techniques. Common adaptation and mitigation strategies in response to building vulnerabilities associated with climate change risks are then reviewed. Risk in this context refers to the probability of occurrence of extreme temperatures and vulnerability as the probability of the building sector being exposed to the risk [26].

3. Weather Files

Buildings are a significant contributor to global warming, and their performance is highly vulnerable to climate variations. Therefore, it is essential to anticipate their performance under the changing climate [27]. A majority of the building simulation tools require weather files as input data [28]. Typical Year (TY) weather files which represent past weather observations are commonly used to avoid using multiple single year weather data [29]. There are two main ways to produce a TY. One is by using a whole year or 12 consecutive months as a representative of the historical observations, and the other is the selection of months by different criteria in which would combine to a whole year [20]. A brief summary on the most commonly used TY files is presented below.

3.1. Current TY Files

Depending on the amount of historical data available, location and the purpose of the data, different methods of typical weather data creation exist (Danish, Festa & Ratto, Finkelstein & Schafer, etc.). Some of the most common types of TYs are Typical Meteorological Year (TMY), Test Reference Year (TRY), Example Weather Year (EWY), Weather Year for Energy Calculations (WYEC), and Design Summer Year (DSY). The TYs differ in their method for selecting representative months that are concatenated to produce a typical year. These sets of data are useful for designing buildings and for comparing their performance in different locations or against different types of buildings.

The TMY file contains diurnal and seasonal variations that reflect the climate for a location and is mainly used in North America [28]. The first set of TMY files was created using data (1952–1975) from 248 locations in 1978 using National Climate Data Center (NCDC) and uses a Finkelstein & Schafer (FS) approach, which is an empirical selection of the typical months out of several years of historical observation. TMY2 data were an updated version of the primary TMY using data from 1961 to 1990 and were presented in 1994 [30]. The most current data sets are TMY3 which uses the input data from 1976–2005, 1961–1990, and 1991–2005 of the National Solar Radiation Data Base, which contains the data for 1020 locations [31]. The TMY3 files contain 68 variables such as global horizontal radiation, direct normal radiation, total sky cover, dry-bulb temperature, relative humidity/dew-point temperature, and wind speed/direction [28].

The European Commission of Energy Efficiency and Renewables provides TMY files worldwide using an updated database from 2005–2015 [32] with a data source obtained from the Satellite Application Facility on Climate Monitoring and European Centre for Medium-Range Weather Forecasts. The TRY and DSY were presented by the Charted Institution of Building Services Engineers in collaboration with Exeter University which are available for 14 locations around the UK. The process of choosing a TRY is similar to the TMY but with different weighting factors (i.e., the importance of each weather parameter). The DSY uses a simpler method. Instead of using average months, the DSY uses a single continual year with the third hottest summer. The main issue of this method is that it does not consider wind speed or solar radiation. However, there have been many efforts to improve these types of files such as the development of the Probabilistic of Design Summer Year (PDSY), the Summer Reference Year (SRY), the Extreme Meteorological Year (XMY), Untypical Meteorological Year (UMY), and Hot Summer Year (HSY). The details of each are presented by [20]. The WYEC selection of months is based on temperature, using the closest value to the long-term mean temperatures. In this method, wind speed is not considered. For free running buildings, this would not offer a suitable method for weather data selection [33].

The use of any of these methods is limited to the amount of data available and the location of weather stations. Sometimes data extracted are from weather stations that are far from major cities that cannot be an exact representative of the local area and where factors such as urban heat island can present discrepancies [34]. Alternative measures to overcome the lack of data exist, such as extracting data from other weather stations closest to the area under examination, using regression methods to estimate data from the years that are not available; using cloud cover data (for the case of solar radiation), and using data from satellites [35]. A summary table of selected research on TY files is presented in Table 1.

Table 1. Selected literature on creation and modification of Typical Years (TYs).

Ref	Proposition	Main finding(s)	Location
[36]	The effect of using different weight factors	Equal weight factors have the best correlation among ranks.	Malaysia
[37]	Proposed a new extreme meteorological year	A combination of more than one typical and two extreme years are a suitable fit to building analysis.	USA
[38]	Using cloud cover as an alternative for daily solar radiation	Good agreement between the long-term values of conventional method and the proposed.	South Korea
[39]	Developed a typical meteorological year for Hong Kong	Good agreement between long term observation and TMY file developed for building consumption.	Hong Kong
[40]	RUNEOLE typical weather tool	Developed a new code to create weather sequences for building applications.	Global
[41]	New weather generator	A weather generator independent of the location and can be adapted to local climate change.	Global
[42]	Created TMY for Iraq	Created TMY for the location of Iraq using the FS method.	Iraq
[43]	Combined the Danish method and Festa–Ratto method	The combination of methods showed better long-term average data.	China
[34]	Compared DSY and TRY within building	TRY is not accurate to derive indications of the average energy use and DSY tends to underestimate level of overheating.	UK

3.2. Future Weather Files

The American Society of Heating, Refrigerating, and Air-Conditioning Engineers (ASHRAE) states that typical weather data should not be used to assess building performance in the future [44]. Generating future typical weather data for building design tools is mostly done by different synthetic weather generators or by statistical techniques such as the morphing procedure [29]. Due to the limitations of historical weather data, synthetic weather generators are more prevalent. Synthetic weather data resembles historical weather behavior and gives insight about cases where data are not significant or are not available; they can simulate meteorological variables for different time periods. The WMO suggests an averaging period of 30 years for defining the baseline climate, which can be challenging if not enough historical weather data is available. Weather generators can be used to produce enough data to assess the probability of occurrence of each variable in the future [20] (e.g., WGEN, CLIGEN, ClimGen, CRU-WG, Met&Roll, WeaGETS, and the KnnCAD). Building energy simulator tools commonly used in the U.S. require weather files in the format of TMY and EnergyPlus Weather (EPW) files. The EPW file is used by the energy simulation modeling software developed by the Department of Energy (DOE). They are a type of weather file that compile with the TMY file dataset. There exists a rich body of research on the creation of future weather data used in building performance analyses and weather generators capable of providing such spatial and temporal requirement which take into account emissions scenarios [45]. A summary of selected research on future weather files for building analyses is presented in Table 2.

Table 2. Summary of literature on generation and modification of future hourly weather files for building applications.

Ref	Summary	Location
[27]	Modified the TRY by increasing temperature steadily for each season. Air humidity was calculated using the psychometric chart and by assuming relative humidity will face no changes.	Australia
[46]	Presented a method for creation of future probabilistic years.	UK
[47]	Merged GCMs output of projected monthly parameters under two emission scenarios for three periods to a TMY file using the morphing procedure.	Hong Kong
[48]	Proposed a new DRY as a substitute for DSY that could suitably account for extreme weather conditions for both summer and winter.	UK
[49]	Compared future weather data produced by the output from the RCM and morphed data from GCM.	UK
[50]	Physically downscaled the results from the GCM to predict local future climate.	Japan
[51]	Presented a method to develop future hourly data based on long-term regional and short-term observations using the morphing technique.	China
[52]	Presented a new algorithm for the creation of hourly temperature data for the UK called the Quarter Sin Method, which uses daily temperature parameters.	UK
[53]	Reviewed weather generating methods of extrapolating, imposed offset, stochastic, and global climate models, and presented a comprehensive framework to generate future hourly weather data.	Australia
[54]	Discusses how Ersatz Future Metrological Year (EFMY) climate files are created.	Australia
[55]	Applied the morphing process to weather data prepared by the OZClim simulation tool.	Australia
[56]	Presented a method to construct hourly weather file for temperature, relative humidity, cloud cover, and solar radiation from the UKCP09 data.	UK
[57]	Cloud Radiation Model (CRM) was proposed as an alternative method when using the weather generator. In addition, suggested using only a shift for mean temperatures when using the morphing technique.	UK
[58]	Used the TMYs extracted from Accurate and applied the morphing procedure based on the predictions of three GCMs for temperatures increasing from 0-6 with 0.5 intervals.	Australia
[59]	Introduced a new weather generator which produces Energy Plus Weather (EPW) and TMY files projected to several future time slices for two IPCC AR5 emission scenario.	US
[60,61]	Developed a new weather generator that produces synthetic weather time series for the US and any location worldwide based on the IPCC AR5.	US
[62]	Presented a method to synthesize weather data derived from RCMs.	Sweden
[63]	Developed a technique called "morphing" to create future hourly weather data.	Global

In addition to Table 2, several weather generators exist that produce future hourly weather data, such as the Urban Weather Gen (UWG) [64], the Advanced WEather GENerator (AWE-GEN) [65,66], the Climate

Change World Weather Generator (CCWorldWeatherGen) [49,67], Meteonorm, and WeatherShift. The CCWorldWeatherGen, developed with Excel, uses the morphing procedure to downscale the outputs of a GCM. Belcher et al. (2005) developed a method called "morphing" to create future hourly weather data to be used in buildings thermal simulations [63]. The morphing technique uses shifting (same variance, different average) and stretching (same average, different variance) on the monthly averages of the weather variables. For instance, for dry bulb temperature, a combination of both is applied: both its mean (a shift) and diurnal changes (a stretch) are transformed. Jentsch et al. (2008) used this method to develop an accessible tool called the CCWorldWeatherGen [67]. The CCWorldWeatherGen uses the Hadley Center Coupled Model Version 3 of the Atmospheric-Ocean GCMs datasets and transforms present EPW or TMY files into future EPW or TMY files. It generates future weather files that capture average weather conditions of climate scenarios while preserving realistic weather sequences for any location around the world. Typical weather data for three future time slices are produced (2020, 2050, and 2080) and for the TAR A2 emission scenario. The CCWorldWeatherGen tool is based on the work of the Sustainable Energy Research Group. The Meteonorm software is a stochastic weather generator that uses an average of all available climate models in the IPCC AR4. It contains a comprehensive climate database which are derived from the Global Energy Balance Archive and WMO and NCDC [54], and can generate typical weather files for two periods of 1981–1990 and 1991–2010 worldwide. In addition, it uses three emission scenarios (A1B, B1, and A2) from the IPCC AR4 and produces outputs in various formats (e.g., TMY and EPW) for nine future time slices (2020-2100). The WeatherShift tool uses a probabilistic approach to create future hourly weather data using two emission scenarios (RCP4.5 and RCP8.5) from the IPCC AR5 for three future time periods (2035, 2065, and 2090). The AWE-GEN was created by the University of Michigan in 2007 and can produce hourly weather data from meteorological stations in the US [65]. It can generate hourly data for ten locations in the US and one location in Italy. The AWE-GEN weather generator is MATLAB-based and can reproduce low and high frequency characteristics of meteorological parameters. Data produced by this weather generator, however, are in raw format that need to be converted to either TMY or EPW files for building simulations. The UWG is also a MATLAB-based simulator that estimates hourly urban air temperature and humidity using weather data from local weather stations. It also captures urban heat island effects. Scholars have used these methods to assess the building performance under future climate conditions. Creating, modifying, and evaluating future weather data for the use of the built environment requires careful attention. There are ongoing studies to eliminate the uncertainties generated from future weather variabilities. In addition to the TY files, most building simulation tools require the use of design condition file, also known as Design Day (DD) files to size building equipment and evaluate their effectiveness under the changing climate. A brief explanation of the DD files is presented as follows.

3.3. Design Day

A design day describes a period with maximum conditions for which the Heating Ventilation and Air Conditioning (HVAC) system was designed to function (operational peak conditions) to maintain indoor conditions. DD files contain a statistical description of monthly and annual weather and are based on different percentiles for warm (0.4%, 1%, and 2%) and cold (99.6% and 99%) seasons [68]. The percentiles for cold seasons define outdoor conditions for a parameter and location which stays above the 99.6% and 99%, and for a warm season, defines outdoor conditions that stays above 0.4%, 1%, and 2% for all hours of the year. The information provided in a design day file consists of required weather parameters for sizing HVAC equipment for heating and cooling. For cooling, the DD files contain the 0.4%, 1%, and 2% dry bulb and its mean coincident wet bulb (MCWB) used to size chillers and air conditioners. The 0.4%, 1%, and 2% wet bulb and its mean coincident dry bulb and wet bulb are used for designing cooling towers and other evaporative coolers. These are especially useful for humidity control applications, such as desiccant cooling and dehumidification, cooling-based dehumidification, fresh-air ventilation systems, and enthalpy systems. For heating applications, the data contains the 99.6% and 99% dry bulb (DB) which is used to size heating equipment. The 99.6% and 99% dew point and its mean coincident dry bulb is used to size equipment for humidification. In addition, the mean coincident wind speed and prevailing coincident wind direction of the 0.4% DB which is used for estimating peak loads due to infiltration. The current design day files available for the United States are updated to 2013 and very few descriptions regarding the use of future scenarios for design day files are available. Without DD files to drive equipment modernization in the future, an increase of heating consumption projections in addition to excessive cooling requirements [69] is anticipated.

4. Building Performance

In urban areas, increased population growth and energy demand in buildings have resulted in greater energy consumption thereby driving the global share (75%) of GHG emissions [15]. Inefficient building construction and equipment and increased GHG emissions are impacted by climate change. Climate change presents not only changes in weather conditions but also imposes uncertainties on building performance. A building's operation is subject to several driving forces such as climate, site and location, geometry, façade and fenestration, architectural design, internal loads, ventilation systems, heating and cooling equipment, and control units. In this section, climate is considered to be the primary driving force and whole building energy performance under the changing climate is reviewed. The significance of other factors (e.g. façade and fenestration improvements, internal loads, etc.) are considered as a response to the primary driving force (the changing climate). During its 50–100 years lifespan, a building may change its operational requirements [70]. Therefore, it is necessary to develop analytical methods to model building performance under future scenarios in response to climate change.

4.1. Energy Assessment

Sustainable building design has the potential to reduce GHG emissions more aggressively compared to other sectors [71]. The driving forces behind sustainable buildings are cost, energy efficiency, and thermal comfort, which must be satisfied in the present as well as under future conditions [72]. Common ways to approach this challenge are the use of Artificial Intelligence (AI), the degree-day method and the use of building energy simulation tools. AI-based approaches such as neural networks [73], fuzzy logic methods [74], and genetic algorithms [75], are used to forecast, model, and control [76] building consumption [77], along with evaluating conservation measures [78] and thermal comfort [79]. The degree-day method is a common way to measure seasonal severity and its impact on building energy consumption [80]. The degree day measures the number of days that the mean of the highest and lowest temperature of the day is higher (for cooling degree days) or lower (for heating degree days) compared to the base temperature. The base temperature is not the set-point temperature of the indoor environment, but the outdoor temperature at which the heat loss from the building equals the heat gain. It may vary depending on the environment, building type, purpose, and thermo-physical properties of the building [80]. The degree day method is also used by the DOE to categorize climate zones across the U.S. in addition to temperature and humidity.

In 2017, approximately 40% of the total energy consumption in the U.S. came from residential and commercial sectors [81]. Results from US Energy Information Administration's 2012 Commercial Buildings Energy Consumption Survey show that between 1979 and 2012, the number of commercial buildings in the U.S. has increased from 3.8 million to 5.6 million. Assessment of energy performance of commercial and residential buildings under future climate scenarios has gained a lot of attention in recent years. Some commonly used building energy simulation tools that have been used to assess future building performance are EnergyPlus, BSim, DOE-2.1E, Tas, TRACE, HAP, Helios, Integrated Environment Solution (IES) Virtual Environment, TRNSYS, eQUEST, and ESP-r [82]. The energy simulation results of buildings modeled under future climate conditions, which stem from climate models for different emissions scenarios, using future weather files generated by means of downscaling techniques, are presented. Table 3 is a summary of the literature which use future typical weather files developed mainly by methods presented in Section 3.2 (morphing or stochastic generators) to assess building energy performance using building simulation tools for different regions. The location column in Table 3 presents the context for the case studies, which were either a continent (e.g., Europe), country, or a city of interest.

Table 3. Summary of research on building energy performance under future climate conditions.

Ref	Tool	Case(s)	Result(s)	Location
[83]	DOE-2.1E	Offices	Increase of 0.4–15% in energy use by 2070 and overheating increase for an outdoor temperature increase of more than 2°C.	Australia
[84]	TRNSYS	NZEB	Due to increased cooling loads, the target of a Net Zero Energy Building (NZEB) cannot be attained for most future years.	Montreal
[85]	EnergyPlus	Office & Residential	Increase of up to 20% in cooling requirements.	Hong Kong
[86]	DIN with a degree day approach	Residential	Depending on renovated factors, climate scenarios and demographic changes, by 2060 cooling demand will remain low unless the amount of A/Cs increase.	Germany
[87]	HELIOS	Residential & commercial	Thermal insulation level will have a critical impact on heating energy demand.	Zurich
[88]	Temperature interval (bin)	Cooling applications	Direct evaporative cooling is incapable of providing thermal comfort in the future and indirect–direct evaporative cooling would be inefficient.	Tehran
[89]	ENERGY2	Offices	High thermal mass buildings can provide better comfort conditions while considering sustainability.	London
[90]	VisualDOE4.1	Offices	A shift towards more electrical cooling consumption, which would lead to higher emissions, is anticipated. In addition, a 1–2°C increase in Set Point Temperature (SPT) has the potential to mitigate GHG emissions.	China
[91]	CALPAS3	Commercial & residential	The increase in annual cooling overcomes the decrease in heating.	US
[55]	AccuRate	Residential	Buildings face a heating and cooling requirement change from 48% to 350%, depending on the location under study.	Australia
[92]	EnergyPlus	Residential & Commercial	The impact of climate change varies greatly depending on the location and the structure of the building. In addition, in the future natural ventilation effectiveness would considerably decline in hot regions.	US
[93]	Degree minute	Residential & NZEB	Net-zero energy buildings are less sensitive than code-current buildings towards climate variables.	US
[94]	ESP-r	Residential & Commercial	No significant relation was found using top-down approach between weather and energy consumption, but the bottom-up approach showed a decrease in heating loads and an increase in cooling loads.	Portugal
[95]	Second-order model	Offices	Natural ventilation would not be enough for cooling requirements; the decrease in heating requirements compensated the increase in cooling demands; building orientation and thermal mass of building are significant.	UK
[96]	IES VE, MacroFlo, SunCast	Public	Possible increase in annual energy consumption of 99% by end of century.	Burkina Faso
[97]	EnergyPlus	Residential	Proposed a resilient design for local areas.	UK
[98]	-	School & residential	Behavioral adaptations are as effective as physical/architectural changes to combat overheating.	UK
[99]	DOE4.1	Offices	External thermal insulation of walls would not be effective. Better options are lowering solar heat gain through windows, lowering Light Load Density (LLD) and improving the COP of the chiller.	Hong Kong
[100]	IES	Residential & Commercial	A linear relation between indoor and outdoor temperatures was found. Solar heat gains play a crucial role in thermal comfort.	UK
[101]	ESP-r	-	Proposed a regression method to relate climate variables with the internal temperatures.	UK
[102]	SAP, RdSAP, IES-VE	Residential	Assessed overheating using different simulating tools; different overheating methodologies can produce significantly different outputs; a Low Carbon Futures (LCF) probabilistic approach was presented.	UK
[27]	DOE-2.1E	Offices	Solar radiation has the most effect on building energy performance.	Australia
[47]	Energyplus	Office & Residential	Increased energy consumption is expected, compared to the baseline weather data.	Hong Kong
[103]	Energyplus	Residential	Overheating studies need to consider the variability of building performance under regional weather variations.	UK
[104]	Matlab	Residential	Using the downscaled weather data from [62] results for heating and cooling showed good agreement with the results from the original weather data with the advantage of accounting for extreme conditions.	Sweden
[50]	TRNSYS	Residential	The sensible heat load was predicted to increase by 15%.	Tokyo

Table 3. *Cont.*

Ref	Tool	Case(s)	Result(s)	Location
[51]	Energyplus	Commercial	The largest percentage increase of whole-building energy demand for an office building, hotel, and shopping mall are respectively 2.6%, 3.1%, and 1.4% by the 21st century.	China
[105]	EnergyPlus	Residential & Office	Total annual energy consumption range from -3.2% to 14% under the A2 scenario in different regions; however, growing peak electricity poses great risk to future grid.	US
[106]	Building ENergy Demand (BEND)	Commercial & Residential	Presented numerous results on the impact of climate change on peak energy demand over eastern interconnection locations in the US	US
[25]	EnergyPlus	Commercial & Residential	Applied dynamically and statistically downscaled weather data to building prototypes and highlighted the importance of considering extreme conditions	City of Geneva
[107]	EnergyPlus	Mid-income house	Heating and cooling requirements will be up to 59% lower and 790% higher respectively. Sun shading was found to be an effective response to the warming climate.	Argentina
[108]	TRNSYS	Office	An overall increase in energy consumption in a range of 50–119% increase with a relative decrease in heating and increase in cooling.	Europe
[109]	TRNSYS	Two-story detached house	A 26% increase in total sensible heat load and 10% increase in latent heat load is expected by the near future.	Tokyo
[110]	DesignBuilder	Office	The impact of the warming climate to the case study is insignificant	Shanghai
[111]	AccuRate	Residential	Climate change shifts the dominant heating requirement to a more cooling demand and measure to reduce cooling loads become critical	Adelaide

From Table 3, it is apparent that the performance of commercial and residential buildings under future climate has driven most of the research over the last decade. Depending on the location and case under study, the results vary in scale. Some studies revealed the impact of the changing climate to be insignificant (e.g., Germany residential [86] and Shanghai offices [110]). The results of buildings with specific building features also varies, for example NZEBs were found to be effective and less sensitive to the climate conditions in US residential building stock [93] but inefficient in the case of Montreal [84]. However, the majority of the studies showed an increase in total energy consumption: Australia (offices [83] and residential [55]), US (commercial and residential) [91], Burkina Faso (public buildings) [96], Hong Kong (offices and residential) [47], China (commercial) [51], Argentina (mid-income housing) [107], and Europe (offices) [108]. In addition, because climate models predict a warming climate on average, many studies revealed a shift towards increased cooling requirements: Hong Kong (offices and residential) [85], China (offices) [90], Portugal (commercial and residential) [94], Adelaide (residential) [111], UK (residential) [102], and US (offices and residential) [105]. The shift towards cooling evades natural ventilation strategies in some regions: US commercial and residential [92] and UK offices [95]. In addition, an increase in peak energy demand is expected. This poses an important risk to future electricity supply [105,106].

In more recent years, the impact of applying strategies to reduce consumption and increase the sustainability of the buildings is gaining attention. The effect of modernization and consideration of design days, however, has received less attention. Design day files have a direct impact on the building equipment sizing. When assessing buildings under future climate conditions, it is crucial to develop updated design day files that are associated to the weather files and evaluate the impacts considering modernization. The use of both typical weather files and DD files to assess building energy performance is necessary.

Figure 3 shows the relation between TMY files and DD files in assessing building energy consumption and demand for current and future conditions. For instance, in order to assess building equipment deficiencies of an existing building, the use of a current DD file and future DD file is necessary. Conversely, to assess existing building performance under future climate, a future TMY file along with current DD file is required. There is a gap in the literature addressing the combined effects of DD and weather files on future building performance. The next section reviews different conservation measures taken in the literature as a response to climate change.

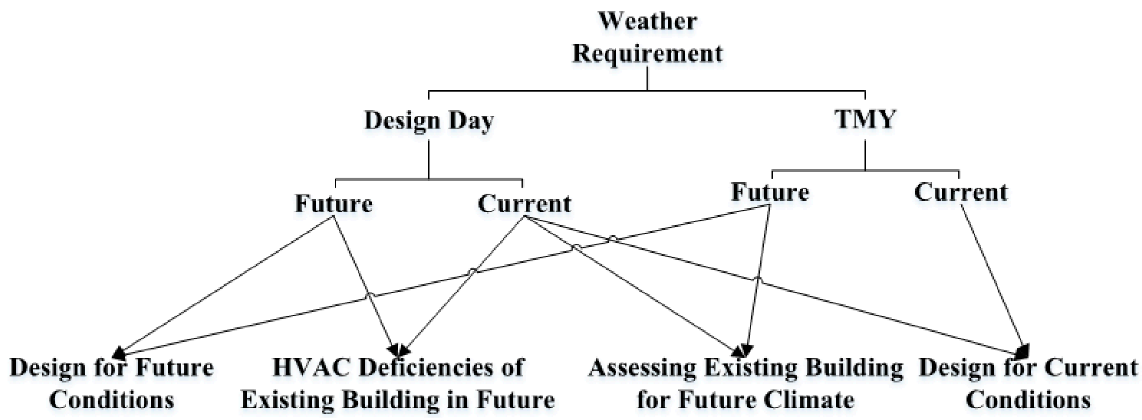

Figure 3. Approach to assess building energy demand and consumption using DD and TMY files.

4.2. Responses

Responses to climate change that are built on practices to reduce GHG emissions are described as mitigation strategies. Responses to climate change impacts are described as adaptation strategies. In either case, responses are either passive or active [112]. Passive responses may encompass bioclimatic concepts such as orientation, insulation, natural ventilation (etc.), used to reduce the thermal exchange between the interior and exterior providing comfort with limited need of heating/cooling and ventilation applications. Active responses are generally comprised of efficient use of HVAC technologies. Nevertheless, there is no single solution that accurately predicts building energy performance under future climate conditions, and the effect of adaptation and mitigations strategies may vary from case to case [113]. Instead, a set of adaptation and mitigation strategies are required for resilience planning in the built environment [97].

Programs such as Leadership in Energy and Environmental Design by the U.S. Green Building Council have addressed mitigation requirements for buildings [114]. However, it is necessary that adaptation and mitigation strategies towards climate change be introduced to current standard codes and policies for building designers. Standards need to be developed to enhance adaptive capacity, to suggest the range of acceptable changes, and to optimize occupant satisfaction [115]. For the latter, thermal comfort can vary with air temperature, humidity, wind velocity, and clothing, and may differ from person to person depending on their metabolic rate. The environmental variables can be controlled by designers and are standardized for all occupants. However, the metabolic rate of the human body changes from person to person. In addition, the ability of a person to tolerate different indoor conditions varies. This requires deeper scrutiny and presents high uncertainty in developing adaptive responses towards climate change. Strategies in the literature to reduce building vulnerability and improve thermal comfort are summarized in Table 4. The impacts of the responses vary across geographical location and case under study which reflects the complexity of identifying optimal measures. The uncertainty of the response factors themselves also impacts the outcomes. For example, Wang et al. (2012) showed the annual site energy of office buildings in the US varied with a range of −11.3% to 6.8% from plug load improvements, −5.3% to 8.4% from lighting control measures and a −5.7% to 9.5% for VAV damper minimum setting control [116]. Coley & Kershaw (2012) reflect input variations by presenting different percentiles of outcomes. They showed for a school in UK by 2050 the 50th percentile of their results yielded a −1.25 °C, −1.23 °C, −0.45 °C, −4.8 °C and −0.03 °C reduction in internal temperatures when implementing shading, solar control glass, earlier day schedules, night ventilation and window opening respectively [98]. Many of the factors presented in Table 4 are viable response strategies. For example, Frank (2005) showed for office and residential buildings in Zurich, improvement in thermal insulation reduces heating demand by 81% [87]; Holmes & Hacker (2007) showed that night cooling can reduce hours above 28°C by 40% [89]; Wan et al. (2012) demonstrated that reducing Window to Wall Ratio (WWR) for a case in office buildings in China resulted in up to 5% reduction in annual average building energy use [90]; Chow & Levermore (2010) suggested using Phase

Change Materials (PCM) as a response to the changing climate [95]; and Wan et al. (2011) concluded that a COP of 5.5 would be required for the case of office building in Hong Kong to alleviate the climate change impacts [99]. The effect of a combination of measures is also assessed by scholars [89–91,95]. For example, Loveland and Brown (1996) showed for the case of Seattle a 43% reduction in cooling loads from a combination of LD, insulation and shading measures, which is higher than the cumulative results of each individual response [91].

Table 4. Summary of adaptation and mitigation responses to the changing climate.

Mitigation	Reference(s)	Adaptation	Reference(s)
Thermal insulation/capacity	[87,89–91,98–100,117]	Shading	[89–91,98]
Natural Ventilation (NV)	[89,95,118]	Solar control glass	[98]
Window and Wall U-Value	[90,95,98]	Night ventilation	[89,98]
Window to Wall Ratio (WWR)	[90,119]	Window opening	[98,100]
Light and/or plug-in equipment	[90,91,98,116,117,119]	Earlier day schedules	[98]
Chiller Coefficient of Performance (COP)	[90,98,99,119]	Setpoint Temperature (ST)	[90,98,116,117,120]
Orientation	[95,100]	Adaptive behaviors	[115]
Building size	[100]	Clothing standards	[100]
Infiltration rate	[100,119]	Night setback	[116]
HVAC operations	[116,120]	Metabolic rate	[119]
Controlled ventilation	[116,120,121]	Overhangs	[117]
Solar Heat Gain Coefficient (SHGC)	[119]	Cool roof	[122]
Equipment Efficiency (EE)	[119]	User behavior	[123,124]
Combined technologies	[125]	Population distribution	[126]

While a survey of building industry representatives highlighted the importance of adaptation strategies in buildings [127], most of the research conducted in response strategies consist of climate mitigation rather than adaptation. A balance between adaptation and mitigation is needed. However, when applying adaptation and mitigation it is necessary to understand incremental [128], transformational [129], synergies, trade-offs, and conflicts of the response measures [112]. For instance, the impact of applying mitigation measures may result in a higher reduction in energy consumption all together (a synergy), or an increase in energy consumption compared to the impact of each measure individually (a conflict), or a competing result necessitating re-evaluation of priorities (a trade-off). In many cases, it is difficult to draw a line to distinguish between adaptation and mitigation strategies. For instance, some adaptation measures may have a mitigating outcome and present co-benefits. Also, adaptation strategies should not be confused with coping strategies, which are short term responses that individuals take temporarily [130] (i.e., clothing, schedules).

The literature shows useful information in terms of case studies (sectors under study) and the effectiveness (i.e., reduction in consumption) of different response strategies. These, however, could benefit from an explicit functional unit (i.e., tons of CO_2) to contextualize the overall impact of the response. Most studies lack the spatial and temporal effect of the responses and measures to monitor the impacts. For instance, it is unclear if the adaptation and mitigation strategies can be aggregated for regional or global benefits. It is also less well known whether the strategies can be realized over a long period of time [131].

Overall, the impact of global warming on buildings may vary for different regions. For instance, subtropical regions may face overheating in summer and result in increased energy consumption and thermal discomfort. Even in cold climate regions, the impact of increased overheating in summer outweighs the impact of moderate winters in terms of energy consumption. These impacts complicate the uncertainties of assessing building performance and may require a case by case study to enhance our understanding of the impacts. The next section reviews existing uncertainties and describes strategies to address them.

5. Uncertainties

Most buildings were constructed before adaptation or mitigation standards or regulations were implemented, and therefore, strategies to improve their energy performance over time and in response to a changing climate are required [132]. This means new methods are required to provide information to designers to make decisions that guide design and performance. However, what decisions will yield optimal results? There is a lack of information or a lack of knowledge about the consequences of design decisions for buildings that will operate 50 to 100 years in the future [132]. Building simulation tools might predict future building conditions, providing a general understanding of the energy and thermal performance of the structure. However, what are the most effective strategies to ensure energy conservation or thermal comfort? The decision making process is not trivial when changes in the frequency, extent, timing, and rapidity of hazards (i.e., extreme temperature) or the amount of uncertainty in the output are very high [132].

Uncertainty analysis in this context reflects how the uncertainties in the input parameter is propagated in the output. It can provide reliability to the design parameters for the overall design. Uncertainties can be due to the building simulation technique, the building's physical characteristics [119,123,133], user behavior [123], the method of TY generation, data source, or availability of historical data, the emissions scenarios, climate models, initial conditions, natural climate variability, or downscaling techniques [21,46,116,133,134]. A summary of potential uncertainties in conducting building performance assessment by means of downscaled weather data and building simulation tools is presented in Figure 4.

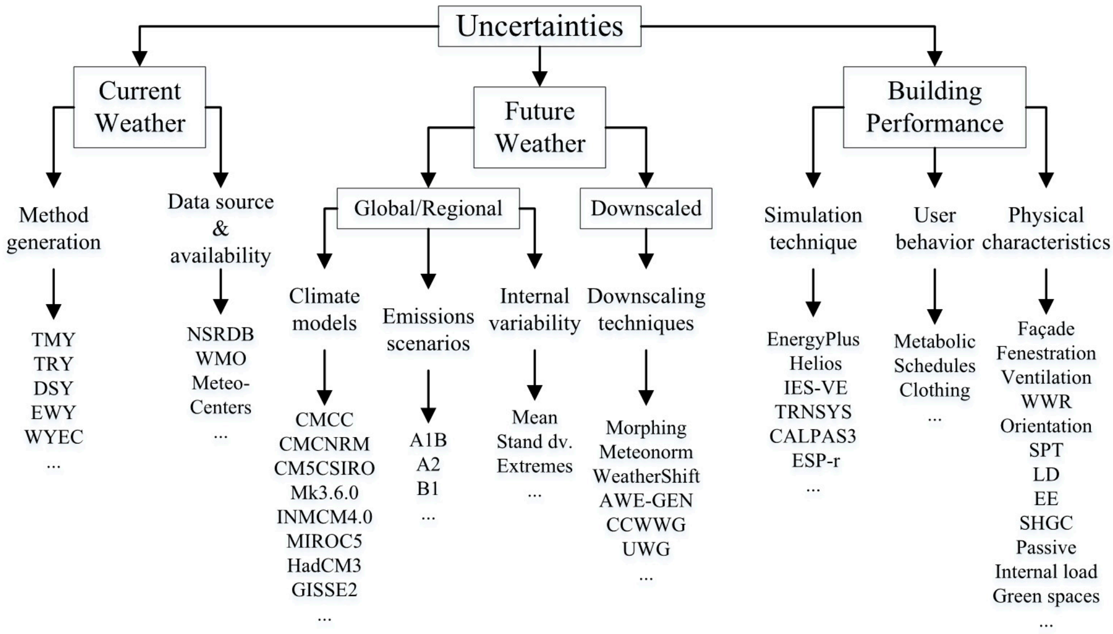

Figure 4. Summary of uncertainties in conducting building performance assessment.

Efforts to partition the total uncertainty of the output of the climate models to their sources are ongoing (e.g., using the Analysis of Variance (ANOVA) model). Decomposing uncertainties of different climate parameters such as global mean air surface temperatures [135–137] and regional precipitation levels [138] is a way of reflecting the total uncertainty into its sources. In the near future, uncertainties due to the output of climate models are dominant, while in the end-century, scenario uncertainties become dominant [135,136,138,139]. This is mainly due to socioeconomic assumptions used to develop emissions scenarios. Different scenarios can be used to describe a range likelihood of occurrences [140]. For future climate projections and uncertainties due to emissions scenarios, the probability functions from all available climate scenarios can be considered [141]. Initial conditions are often set as preindustrial conditions, which represents a period before changes in the climate were not attributable to human activity. However, there is little information from that period about specific climate variables, and simulations are used to generate hypothetical initial conditions and referred to as control runs [21]. Uncertainties that are due to the response of different climate models can be treated by using output results from different GCMs/RCMs [141]. The uncertainty of climate variability (i.e., in mean and standard deviation) can be described by probabilistic approaches [141]. This uncertainty increases when applying weather files for regional scales and hourly time periods to be used in building simulations [142]. The use of statistical techniques in addition to the dynamic approaches of assessing building performance can provide a range of possible outcomes that could take into account uncertainties in this part. This would require methods to narrow down the uncertainty in order to make a critical decision.

One way to address this would be to propagate the effect of the input uncertainty by creating a set of probability distributions. Hayes (2011) [140] presents five ways that a probabilistic approach can be implemented: expert opinion, standard parametric results, bootstrapping, maximum likelihood, and Bayesian approach. Bootstrapping is a method that can be used when the population is unknown and only sample data are available. The method would resample the data to characterize its variability and produce a population distribution of the sample given. In other words, it propagates uncertainty in the inputs through the model to characterize uncertainty in the output. However, this method requires the existence of two important elements: first, the input parameters and second, a dynamic/statistical model to be used to propagate the results. When there is doubt about the appropriate distribution (and input parameters) to be used, then different distributions should be assumed and their effect should be analyzed. To test whether a distribution suits the data, a comparison can be made to choose the best fit [143]. Or this can be done by determining the statistical parameter with distribution fitting techniques. For instance, one method is to minimize the difference between the empirical Cumulative Distribution Function (CDF) and the CDF of the fitted distribution. However, probabilities are not always easy to assess. This adds to the uncertainty of the approach and requires deep understanding of the variables under study to assess specific probabilities. One is to assume each variable has an equal chance of occurrence. Another way is to set up a survey among scientists to assess their prediction in the range of the possibilities [132]. Each step on the propagation method adds to the total uncertainties.

The statistical model for buildings can be developed by producing enough energy outputs from different climate inputs by using dynamic simulation tools. Then the model must be regressed between weather variables and the energy outcomes to associate the input variables to the outputs of the building simulation tool. The regression model can be used as the second element of the uncertainty propagation. Figure 5 shows a sample approach to propagate the uncertainties for building performance under future climate conditions. The arrows reflect a step that is part of the uncertainty analysis but also adds to the uncertainties.

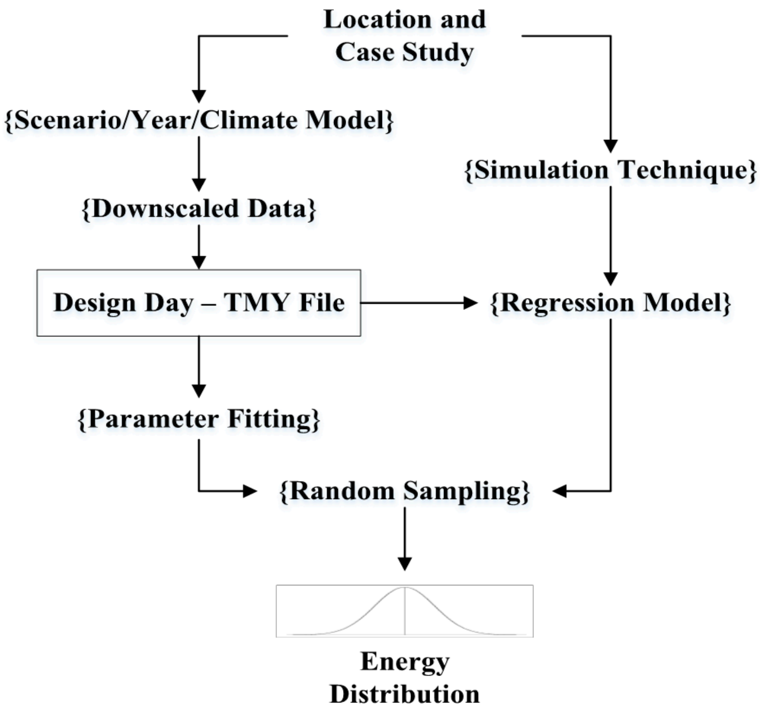

Figure 5. Sample probabilistic approach to propagate building energy uncertainties.

In Figure 5, the first step is to generate enough future TMY and DD files to capture the future climate conditions based on different scenarios for different time periods (i.e., 2020, 2050, and 2080) using either a morphing technique or weather generators. Using statistical parameter fitting techniques, a distribution can be fitted to the weather variables (i.e., the distribution of dry bulb temperature). The generate weather files can then be used as input file to a sample building using a building simulation tool (e.g., EnergyPlus), and large number of outputs (e.g., electricity consumption) can be generated. The association between the output (energy) and input (weather variables) can be determined using statistical regression models (e.g., linear or nonlinear). With the model and distribution determined, a random sampling technique (i.e., Monte Carlo [144]) can be used to propagate the input uncertainty to the output and draw a range of possible occurrences in the future. Probabilistic information within future projections reflect the likelihood of occurrence of future climate. This method can be done for any other variable depending on the sensitivity of that variable to building energy performance. In general, while imperfect, sampling-based methods are commonly used to propagate the uncertainties.

6. Conclusions and Discussion

Today's buildings must be future-proofed against climate impacts. To do this, it is necessary to understand how buildings will perform in the future and to develop and refine climate resilience policies to mitigate climate risks and vulnerabilities. Conventional building energy assessment approaches do not consider the changing climate. It is necessary to develop new strategies and methods to advance resiliency of the building and the ongoing sustainability of the built environment. This article reviewed current approaches by scholars to understand how buildings will perform in the future. Methods to develop granular spatial and temporal weather files that can be incorporated in building simulation tools were presented and their impact on the building stock along with adapting and mitigating measures were reviewed. It was found that there is a gap in the literature on the effect of equipment modernization and the consideration of design days. Design day files have a direct impact on the building equipment sizing. When assessing buildings under future climate conditions, it is crucial to develop updated design day files and weather files, and to evaluate the impacts of modernizing HVAC equipment.

Uncertainties regarding the development of the typical year files, climate models, emissions scenarios, internal weather variability, downscaling techniques, building simulation, user behavior, and physical characteristics of buildings were presented (and summarized in Figure 4). Common methods to reflect, propagate, and partition uncertainties were described. A sample approach to uncertainty analysis using downscaled future typical weather files in building simulation tools was presented. In uncertainty analysis, a probabilistic approach that reflects all possible scenarios is necessary to obtain a comprehensive understanding of the current state and possible outcomes in the future. This provides decision makers and designers with knowledge and information to select a suitable fit for their design goals. Overall, given the level of uncertainty regarding future climate conditions, current approaches are not adequate. The building design and analysis research community must drive the effort to integrate climate models into meteorological weather data [145]. This is needed to increase awareness of how buildings will need to be designed and operated in the future. Moreover, a comprehensive assessment of building typologies under extreme conditions [25] to guide future building codes and standards [146] is necessary. These efforts must also include an understanding of adaptive capacity under extreme conditions [147], as well as economic feasibility [148,149] assessments of potential response factors. Advancing climate-ready decision making [150] will promote resilience processes and policies for buildings under climate change.

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Abbreviations

GHG	Greenhouse Gas
IPCC	Intergovernmental Panel on Climate Change
UNEP	United Nations Environmental Programme
WMO	World Meteorological Organization
TAR	Third Assessment Report
AR4	Fourth Assessment Report
AR5	Fifth Assessment Report
GCM	General Circulation Models
RCM	Regional Circulation Models
RCP	Representative Concentration Pathway
NARCCAP	North American Regional Climate Change Assessment Program
TY	Typical Year
TMY	Typical Meteorological Year
TRY	Test Reference Year
EWY	Example Weather Year
WYEC	Weather Year for Energy Calculations
DSY	Design Summer Year
NCDC	National Climate Data Center
FS	Finkelstein & Schafer
NSRDB	National Solar Radiation Data Base
ECEER	European Commission of Energy Efficiency and Renewables
CM SAF	Satellite Application Facility on Climate Monitoring

ECMWF	European Centre for Medium-Range Weather Forecasts
CIBSE	Charted Institution of Building Services Engineers
PDSY	Probabilistic of Design Summer Year
SRY	Summer Reference Year
XMY	Extreme Meteorological Year
UMY	Untypical Meteorological Year
HSY	Hot Summer Year
ASHRAE	American Society of Heating, Refrigerating and Air-Conditioning Engineers
DOE	Department of Energy
EPW	EnergyPlus Weather
CRM	Cloud Radiation Model
EFMY	Ersatz Future Metrological Year
UWG	Urban Weather Gen
AWE-GEN	Advanced WEather GENerator
CCWorldWeatherGen	Climate Change World Weather Generator
HadCM3	Hadley Center Coupled Model Version 3
SERG	Sustainable Energy Research Group
GEBA	Global Energy Balance Archive
WMO	World Meteorological Organization
DD	Design Day
HVAC	Heating Ventilation and AirConditioning
MCWB	mean coincident wet bulb
DB	Dry Bulb
COP21	Conference of the Parties
SDG	sustainability development goals
NZEB	Net Zero Energy Building
LLD	light load density
LCF	Low Carbon Futures
LEED	Leadership in Energy and Environmental Design
USGBC	U.S. Green Building Council
WWR	window to wall ratio
SPT	set point temperature
SHCG	solar heat gain coefficient
LD	lighting density
EE	equipment efficiency
ANOVA	Analysis of Variance
CBECS	Commercial Buildings Energy Consumption Survey
EIA	Energy Information Administration
PCM	Phase Change Material
CDF	Cumulative Distribution Function

Appendix A

Table A1. Spatial resolutions of the IPCC climate models.

Centre(s)	Model	rcp26	rcp45	rcp60	rcp85
Beijing Climate Center (China)	BCC-CSM1.1	3 hr	3 hr	3 hr	3 hr
Beijing Normal University (China)	BNU-ESM	3 hr	3 hr	-	3 hr
Canadian Centre for Climate Modelling and Analysis (Canada)	CanESM2	6 hr	6 hr	-	6 hr
Centro Euro-Mediterraneo sui Cambiamenti Climatici (Italy)	CMCC-CM	3 hr	-	-	3 hr
Centre National de Recherches Météorologiques (France)	CNRM-CM5	3 hr	3 hr	-	3 hr
Commonwealth Scientific and Industrial Research Organization/Bureau of Meteorology (Australia)	ACCESS1.0	3 hr	-	-	3 hr
Commonwealth Scientific and Industrial Research Organization/Queensland Climate Centre(Australia)	CSIRO-Mk3.6.0	Day	6 hr	Day	6 hr
The First Institute of Oceanography, SOA (China)	FIO-ESM	M [1]	M	M	M
EC-EARTH consortium published at Irish Centre for High-End Computing (Netherlands/Ireland)	EC-EARTH	3 hr	3 hr	-	3 hr
Russian Academy of Sciences, Institute of Numerical Mathematics (Russia)	INMCM4.0	3 hr	-	-	3 hr
Institut Pierre Simon Laplace (France)	IPSL-CM5A-LR	3 hr	3 hr	3 hr	3 hr
Institute of Atmospheric Physics, Chinese Academy of Sciences (China)	FGOALS-g2	3 hr	-	-	3 hr
Atmosphere and Ocean Research Institute (Japan)	MIROC5	3 hr	3 hr	3 hr	3 hr
Met Office Hadley Centre (UK)	HadGEM2-ES	3 hr	3 hr	3 hr	3 hr
Max Planck Institute for Meteorology (Germany)	MPI-ESM-LR	Day	6 hr	-	6 hr
Meteorological Research Institute (Japan)	MRI-CGCM3	3 hr	3 hr	3 hr	3 hr
NASA/GISS (Goddard Institute for Space Studies) (USA)	GISS-E2-R	M	3 hr	M	M
National Center for Atmospheric Research (USA)	CCSM4	3 hr	3 hr	3 hr	3 hr
Bjerknes Centre for Climate Research, Norwegian Meteorological Institute (Norway)	NorESM1-M	3 hr	3 hr	3 hr	3 hr
National Institute of Meteorological Research (South Korea)	HadGEM2-AO	M	M	M	M
Geophysical Fluid Dynamics Laboratory (USA)	GFDL-ESM2M	3 hr	3 hr	3 hr	3 hr

[1] Monthly.

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