Impacts of future weather data typology on building energy performance – Investigating long-term patterns of climate change and extreme weather conditions

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Keywords

Future weather files, typical and extreme weather conditions, climate uncertainty, building performance simulation, climate change, statistical and dynamical downscaling of climate models

Nomenclature

AR	IPCC Assessment Report
ASHRAE	American Society of Heating, Refrigerating, and Air-Conditioning Engineers
BPS	Building performance simulation
ECY	Extreme Cold Year
EPW	EnergyPlus Weather
EWY	Extreme Warm Year
GCM	Global Climate Model or General Circulation Model
IPCC	Intergovernmental Panel for Climate Change
IPCC DDC	IPCC Data Distribution Center
IWEC	International Weather for Energy Calculations
PNNL	Pacific Northwest National Laboratory
RCM	Regional Climate Model
RCP	Representative Concentration Pathway
SRES	Special Report on Emission Scenarios
TDY	Typical Downscaled Year
TMY	Typical Meteorological Year
UKCP09	UK Climate Projections 2009
XMY	Extreme Meteorological Year

Abstract

Patterns of future climate and expected extreme conditions are pushing design limits as recognition of climate change and its implication for the built environment increases. There are a number of ways of estimating future climate projections and creating weather files. Obtaining adequate representation of long-term patterns of climate change and extreme conditions is, however, challenging. This work aims at answering two research questions: does a method of generating future weather files for building performance simulation bring advantages that cannot be provided by other methods? And what type of future weather files enable building engineers and designers to more credibly test robustness of their designs against climate change? To answer these two questions, the work provides an overview of the major approaches to create future weather data sets based on the statistical and dynamical downscaling of climate models. A number of weather data sets for Geneva were synthesized and applied to the energy simulation of 16 ASHRAE standard reference buildings, single buildings and their combination to create a virtual neighborhood. Representative weather files are synthesized to account for extreme conditions together with typical climate conditions and investigate their importance in the energy performance of buildings. According to the results, all the methods provide enough information to study the long-term impacts of climate change on average. However, the results also revealed that assessing the energy robustness of buildings only under typical future conditions is not sufficient. Depending on the type of building, the relative change of peak load for cooling demand under near future extreme conditions can still be up to 28.5% higher compared to typical conditions. It is concluded that only those weather files generated based on dynamical downscaling and that take into consideration both typical and extreme conditions are the most reliable for providing representative boundary conditions to test the energy robustness of buildings under future climate uncertainties. The results for the neighborhood explaining the critical situation that an energy network may face due to increased peak load under extreme climatic conditions. Such critical situations remain unforeseeable by relying solely on typical and observed extreme conditions, putting the climate resilience of buildings and energy systems at risk.

1 Introduction

Building performance simulation (BPS) empowers designers to evaluate a proposed design under the probable climate conditions that a building will face during its lifetime. Weather data defines the external boundary conditions for a numerical building model. Detailed weather data that, as a minimum, includes daily and hourly resolution is required to properly describe the dynamic energy behavior of a building. There have been many attempts over the last 40 years by a number of organizations to create standardized weather files for thousands of locations on the planet [1]. These files are readily accessible to users and have formats that are suitable to be directly used in energy simulation tools [2]. Weather files are usually built upon recordings of actual historical weather data. Different weather files may, however, have different baseline observation periods. These standardized weather files provide BPS users with a single-year of typical weather data that represent typical regional climate conditions, based on a continuous time span of 20 or 30 years of historical observed data. These weather data sets are widely used and represent average conditions well enough. They, however, to a large extent fail to represent extreme weather conditions and to project future conditions, especially at the hourly temporal resolution, as it has been shown by several studies [3], [4], [5], [6]. As a result, a number of methods have been developed to create future weather files for BPS. These have been discussed in a review paper by Herrera et al. [7]. The future weather files are used to study the impacts of climate change on building performance, numerous works on this having been published. Yau and Hasbi [8] reviewed the climate change impacts on commercial buildings and arrived at the trivial conclusion that, in general, buildings in regions with a projected increase in temperature will, in the future, require more energy for space cooling and less energy for space heating. Other studies revealed similar conclusions for case-study buildings in Austria [9], Italy [10], United States [11], China [12], and other locations around the globe. de Wilde and Coley [13] discuss the relationship between climate change and buildings and conclude that the majority of studies on the impact assessment of climate change on buildings look at few performance indicators, such as energy use for space heating and cooling, and the risk of overheating. There are, however, studies of the hygrothermal performance of buildings under future climatic conditions [14], which investigate performance indicators that highly correlate with air temperature and moisture content [15], and that take into account several climate indices such as air temperature, relative humidity, solar radiation and cloudiness [16].

The Intergovernmental Panel for Climate Change (IPCC) created a number of possible scenarios of future anthropogenic greenhouse gas emissions based on given socio-economic storylines, to project future changes in climate for impact and adaptation assessment. The first set of scenarios were introduced in the IPCC Special Report on Emissions Scenarios (SRES) in 1996 [17], [18]. Later, in 2014, the IPCC adopted a new series of emission and concentration scenarios called "Representative Concentration Pathways (RCPs)" [19]. These emission scenarios are the input data used to provide initial conditions for the so-called General Circulation Models or Global Climate Models (GCMs), which are today's most complex quantitative models for forecasting climate change. GCM outputs represent averages over a region or the entire globe with a spatial resolution in the range of 100-300 km^2 and a monthly temporal resolution. These data resolutions are not suitable for direct use in BPS tools that require local weather data with hourly or sub-hourly resolution. Therefore, GCM data need to be downscaled to the appropriate spatial and temporal resolution. Indeed, all future weather information with a spatial resolution of less than 100 km^2 and temporal resolution less than monthly values has been through a downscaling process [20]. There are two main approaches to downscale GCM outputs and generating data with a finer temporal and spatial resolution. These are dynamical and statistical downscaling. After the downscaling process, the generated years of weather data need to be formatted according to a precise template to be readable by BPS tools. One common approach is the method developed by Hall et al. [21] for creating a typical meteorological year (TMY), which is derived from 30 years of weather data recordings. January for the TMY is copied directly from the historical January data that has the closest match to the 30-year average condition for January. This process is replicated for the other months to produce 12 months of the typical weather year. Subsequently, some methods, for example the spline method, are then adopted to smooth and link together the twelve monthly weather data series. One of the main disadvantages of this method on climate change impact assessment is its averaging nature: the generation of a typical weather year neglects extreme weather conditions. We, in the last decade, have experienced some of the warmest years on record [22]. Such conditions highlight the importance of considering extreme conditions in the design and adaptation process of buildings and energy systems for the future conditions. A probabilistic forecast indicates a warmer than normal period for 2018–2022, temporarily reinforcing the long-term global warming trend and increasing the likelihood of intense to extreme temperatures, as happened in summer 2018 in Europe [23]. Failure in climate change adaptation can lead to costly short- and long-term issues [24], such as blackouts due to energy supply disruption [25]. Power failures can leave thousands of buildings without electricity or any means of space cooling, which can be fatal for the elderly, very young, or the chronically ill people. The heat wave of the summer of 2003 in Europe caused more than 70000 heat-related deaths [26]. This is becoming increasingly important as the number of elderly people continues to rise and the predicted occurrence of heat waves increases [27]. These problems partly are arising from the fact that existing buildings are not designed for atypical conditions, and their expected performance is based on most-likely conditions. It makes their performance to fluctuate significantly when outdoor climate conditions fall out of typical conditions. That is why during a heat wave the electricity demand soars and causes the energy systems at risk of failure. Unfortunately, only a minority of scientific works and professional practices test their building design under conditions that include extremes. We draw on the literature and selected studies that used BPS to assess the impact of climate change on the performance of the buildings (Figure 1).

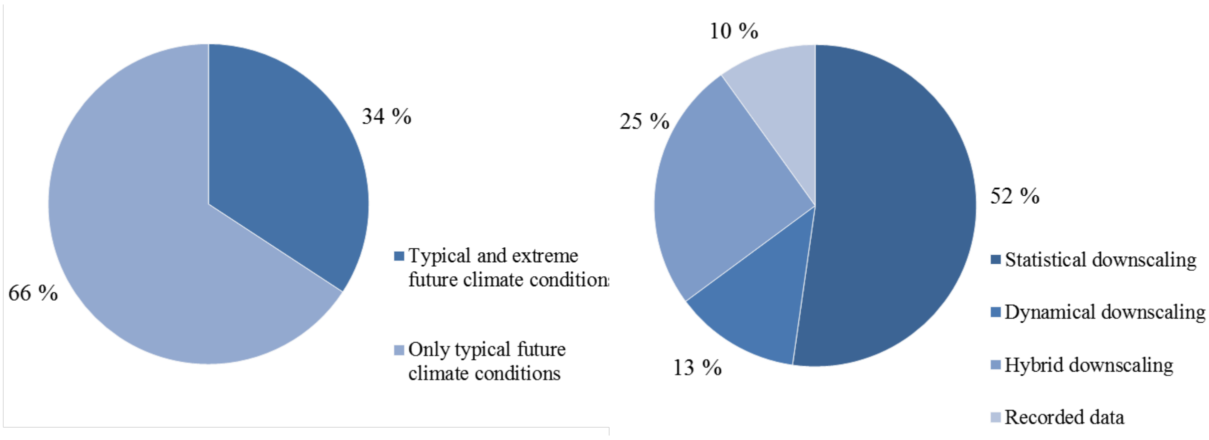

Figure 1 Analysis of literature that used BPS to assess the impact of climate change on the performance of the buildings (111 articles)

Figure 1 was developed from the analysis of 111 scientific papers detected after querying the Web of Science and Scopus databases. All these papers have been published after 2001 and are listed in Annex A. Albeit considering extreme conditions in the design process seems to be obvious due to the increase in their frequency of occurrence and magnitude and also the high cost of possible damages, but according to Figure 1, 66% of the studies (73 articles) are based on only typical future climate conditions. Furthermore, with regards to the downscaling methods used for preparing weather files, 52% (58 articles) are based on statistically downscaled data, 13% (14 studies) used directly data from RCMs and 25% (28 articles) used the hybrid method. These methods are described further in this study. Finally, 10% of the studies (11 articles) used recorded data, which means they used recorded data of an extreme year such as that of 2003 in Europe to study the impact of extremes conditions. It is worth highlighting that 38% of all the 111 studies (42 articles) corresponding to 55% of all the studies that consider extremes (21 out of 38 articles) are from the UK where *Test reference year* (TRY) weather files representing future typical conditions and *near extreme Design Summer Year* (DSY) weather files are provided at national level. These files are generated using data from the UK Climate Projections (UKCP) project [28]. Therefore, it seems that if reliable future weather data sets are available at a national level, the tendency to be used in building studies is very high.

As mentioned, adequate representation of long-term patterns of climate change and extreme conditions is challenging, as there are a number of ways of estimating future climate projections and creating weather files. This study provides an overview of the major approaches for creating future weather data sets based on statistical and dynamical downscaling of climate models. For the first time, the effects of using major available approaches for generating future weather files are studied on the calculation of energy performance of buildings. The building models were simulated in isolation and combined to create a virtual neighborhood representing a neighborhood in Geneva. The investigation critically analyzes the magnitude of the difference between impact assessments carried out using weather data generated by dynamical and statistical downscaling methods. It also investigates the possibility and importance of using extreme weather years in BPS at both the building and neighborhood scales. This will allow understanding the magnitude of the risk induced at large scale by not taking into account possible future climate extremes. The main objective of this study is to provide insight on which is the most reliable future weather generation method to use in building energy simulations, enabling engineers and designers to test their building designs and achieve designs that are less sensitive and more robust against climate changes.

A total number of 74 future weather data files, which include typical and extreme weather years, were generated for the city of Geneva, Switzerland, to be used in the investigation. Geneva was chosen due to the availability of the data and the possibility of having cold winters and warm summers. Geneva furthermore reached a temperature record of 41.5 °C (+5.4 °C above the average temperature) during the summer heat wave in Europe of 2003 [29]. This makes an interesting site to investigate in this work. The generated weather files were used to simulate 16 commercial reference buildings proposed by the ASHRAE Standard 90.1. Each of the buildings was simulated using the 74 weather files, which resulted in a total of 1184 simulation runs. Afterwards, a virtual neighborhood was also created using a combination of the 16 buildings for a total of 85 buildings, to evaluate the impact of the weather file typology on estimating the energy demand at the neighborhood scale.

This paper is divided into five sections. Section 2 provides a short background on downscaling GCM outputs to generate future weather files to us in BPS (Section 2.1), and to creating typical and extreme weather data sets (Section 2.2). Section 3 explains the methodology used for performing the analysis applied in this study, details of the generated weather files, building models, and virtual neighborhood being given in Sections 3.1, 3.2.1 and 3.2.2 respectively. Results are presented and discussed in Section 4, followed by Conclusions in Section 5.

2 Preparing future weather data sets

2.1 Downscaling global climate models

Global climate models (GCMs) are numerical models of the physical processes that characterize the global climate system, including the atmosphere, oceans, cryosphere and land surface [30]. These models are validated against past climate conditions to check if they can simulate the evolution of the climate system by means of running re-analyses like ERA-40 for validation. ERA-40 is a re-analysis of meteorological observations from September 1957 to August 2002 produced by the European Centre for Medium-Range Weather Forecasts (ECMWF) [31]. Once the model is verified and validated, it will set to run (usually from 1870), picking initial conditions and forced by emissions scenarios or Representative Concentration Pathways (RCPs), which are based on different greenhouse gas emission scenarios developed by IPCC [20]. Results of GCMs are expressed at the global or continental scale, and typically use long temporal resolutions such as monthly, seasonal or annual periods. These scales are too coarse for many applications and particularly for the building performance assessment. Direct use of the GCM output in impact assessment is therefore not recommended due to recognized biases [32]. Buildings are affected by the local climate, and some assessment methods may require environmental data even at the sub-hourly resolution [33]. Future weather data sets at finer temporal and spatial resolutions than those provided by GCMs are required to meet the needs of building engineers and designers. As previously mentioned, there are two main approaches to generating future weather data series. These are *dynamical downscaling* and *statistical downscaling.* There is a third approach that consists of a combination of the two approaches and is referred as *hybrid downscaling*.

The flowchart in Figure 2 displays the usual steps of the downscaling process available today.

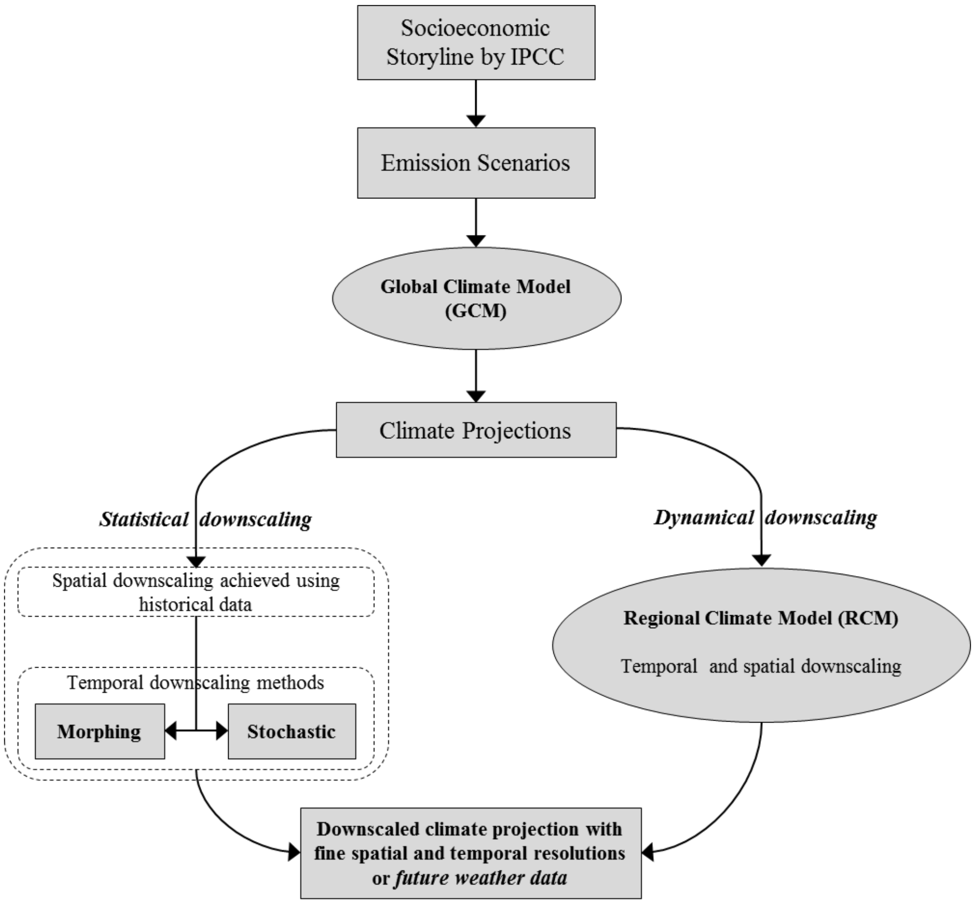

Figure 2. Flowchart of different approaches for preparing climate projection data with fine spatial and temporal resolution suitable to generate future weather files for BPS.

The downscaling process of GCMs provides climate data with higher spatial and temporal resolutions. The procedure hence requires additional information and assumptions, which typically result in a propagation of uncertainties. There are also a number of GCMs developed by different institutes, generating future climate projections. The chaotic nature of the climate system limits accurate interannual prediction of global temperatures [23]. There are several uncertainties that affect any impact assessment of climate change, such as uncertainties in the historical relationship between temperature variability and economic growth, the spatial pattern temperature change associated with the level of aggregate emissions, and the future rate and pattern of economic development [34]. Therefore, probabilistic approaches are usually taken into account for the impact assessment of climate change, considering several climate scenarios and uncertainties. The existence of several models and uncertainties in simulating future climatic conditions is an important challenge which should be considered in impact assessment in all fields. This has been thoroughly investigated in previous works [14], [16] and [35]. There is significant confidence that climate models provide reliable quantitative estimates of future climate change. This confidence comes from the fact that models are based on accepted physical principles and also from their ability to regenerate observed patterns of current climate and past climate change [36].

2.1.1 Dynamical downscaling

Dynamical downscaling derives local or regional climate information using a Regional Climate Model (RCM). RCMs are numerical models that require explicitly specified boundary conditions from a GCM, or an observation-based data set (re-analysis). They simulate "atmospheric and land surface processes, while accounting for high-resolution topographical data, land-sea contrasts, surface characteristics, and other components of the Earth-system" [37]. RCMs generate climate information at a much finer resolution than GCM, down to 2.5 km^2 [38]. This method has many advantages. It however also requires a considerable amount of computational power and large storage for the creation of the data sets. An RCM is nested into a GCM. The overall quality of the outputs is therefore tied to the accuracy of the underlying GCM [39]. Efforts were therefore made to quantify these uncertainties by combining different GCM-RCM pairings and performing series of simulations called 'ensembles'. Examples of such efforts are the ENSEMBLES [40] and EURO-CORDEX [41] projects. The need to consider several climate scenarios rather than just one scenario in the impact assessment of buildings has been highlighted in previous studies [42], [16]. The Rossby Centre Regional Atmospheric Climate Model (RCA4) is used in this study. RCA4 has been running for the European CORDEX domain at two different horizontal resolutions, 50 km^2 and 12.5 km^2. Downscaling of the ERA-Interim reanalysis data are used to evaluate model performance in the recent past climate [43]. The verification process has been performed for the historical period 1961-2005 for which historical forcing was applied [44]. The model is then used to perform simulations for different future scenarios in which RCP scenarios have been applied to prescribe future radiative forcing. For the purpose of this work, the output data from the combination of four GCMs downscaled by RCA4 and forced by two different RCPs (4.8 and 8.5) are used. The details are given in Section 3.1.4.

2.1.2 Statistical downscaling

Statistical downscaling derives estimation of regional or local climate variables from larger-scale climate data using deterministic or stochastic approaches. The difference between the approaches depends on whether an additional noise term for random variability is explicitly included [45]. Until now, the complexity of the dynamical downscaling method and the high level of expertise that is required to interpret the results of the climate simulations have pushed BPS users to favor statistical downscaling. This approach is simpler than dynamical downscaling, however, due to the higher availability of hourly data, which can be directly extracted from RCMs, it is expected that the number of applications for locations worldwide that use dynamical downscaling will increase [46]. The next two sections briefly look into two available approaches (and their assumptions) for statistical downscaling of GCMs.

2.1.2.1 Morphing

The *morphing* downscaling method was proposed by Belcher et al. [47] and applies three transformation algorithms to the hourly values of given weather variables. The algorithms apply changes based on monthly trends and variations of GCM or RCM outputs for a given location. These three algorithms are called S*hift*, *Stretch* and *Combination of shift and stretch*.

1) *Shift* is an additive formulation and adds a predicted absolute monthly mean change (Δx_m) derived from a GCM or RCM to the hourly values of a weather variable in the weather file (x_0) for the month *m*:

$$x|_m = x_0 + \Delta x_m \tag{1}$$

2) *Stretch* has a multiplicative formulation and scales the hourly values of a variable in the weather file (x_0) by a predicted relative monthly mean change (α_m) for the month *m*.

$$x|_m = \alpha_m \cdot x_0 \tag{2}$$

3) The *Combination of shifting and stretching* is a linear combination of the two previous transforming functions. The hourly values of a weather variable in the weather file are both shifted by adding the predicted absolute monthly mean change (Δx_m) and stretched by a predicted relative monthly mean change (α_m) for the month *m*.

$$x|_m = x_0 + \Delta x_m + \alpha_m (x_0 - x_{0,m}) \tag{3}$$

where $x_{0,m}$ is the variable x_0 averaged over month m for all the considered averaging years of future data provided by climate models.

$$x_{0,m} = \frac{1}{24 \times d_m \times N} \sum_{\text{N years}} \sum_{\text{month m}} x_0$$

where *N* is the number of years in the averaging period, d_m is the number of days in month *m*, and 24 hours of a day.

One of the three algorithms is applied, which depending on the weather variable. For example, the first algorithm is used for adjusting atmospheric pressure, the second is used for wind speed, and the third for temperature. A guideline on using the above algorithms for the variables in a weather file is given in [47]. CCWorldWeatherGen and WeatherShift are two available tools. They use the morphing method to create climate change weather files starting from EnergyPlus weather files (EPW). Moazami et al. [48] critically compared the output of the two tools to identify the possible consequences of applying these to BPS. The two tools have differences in some of their calculation assumptions, which are discussed in more detail in Sections 3.1.1 and 3.1.2.

2.1.2.2 Stochastic generation

Stochastic weather models are based on a statistical analysis of recorded climate data. The models can derive all other weather variables [49] using the inputs of just a few independent weather variables (e.g. solar radiation). For example, Meteonorm software is a weather generator that uses the interpolation of the principal weather variables to provide weather data for any site in the world [50]. It provides weather variables such as global irradiance on a horizontal plane at the ground level, dry-bulb temperature, dew-point temperature and wind speed. Values are delivered as monthly and yearly long-term means and data time series at the hourly and minute time resolution are generated stochastically and correspond to typical years. The model can generate hourly weather data that can be used as input for BPS. All noteworthy Meteonorm details are given in Section 3.1.3.

2.1.3 Hybrid downscaling

A hybrid approach can, in some cases, be used to reduce the computational resources and storage space required in dynamical downscaling. It is commonly called hybrid downscaling, the outputs of an RCM being stored at a coarse spatial and temporal resolution and further downscaled using the statistical methods. For example, the climate projections for the UK (UKCP09) provide future weather data on a monthly basis at a spatial resolution of 25 km^2. This data is then statistically downscaled to the hourly and/or daily temporal resolution at a 5 km^2 spatial resolution [28]. Another example is the Integrated Multi-scale Environmental Urban Model (IMEUM) in which climate variables estimated at the city scale by RCM data at a 25 km^2 resolution are statistically downscaled first to the spatial resolution of 1 km^2 and then to the 100 m^2 resolution [51].

There have been several studies on relative performance of statistical and dynamical or hybrid downscaling methods in climate change impact assessments. Fowler et al. [52] provided a comprehensive insight to the choice of downscaling method when examining the impacts of climate change on hydrological systems. Wilby et al.

[53] compared the relative performance of future rainfall projections generated by the range of available downscaling methods. The topic has been also discussed in BPS literature and Table 1 lists and summarizes the main advantages and disadvantages of downscaling methods given in the literature. But there is a lack of work on the effect of using different downscaling methods for generating future weather files on the energy performance of buildings.

Table 1 . Advantages and disadvantages of downscaling methods.

Downscaling method	**Advantages**	**Disadvantages**
Dynamical downscaling using RCM	• Physically consistent data sets across different weather variables [20] • Not constrained by historical data [20]	• Large data sets [20] • Powerful computational resources and expertise required [20]
Statistical downscaling using morphing	• Flexible because it can be applied to the large number of weather files that are available worldwide [54] • Captures localized weather conditions [47], [54], [7] • The method is simple [47] • Low amount of computational power is required [55]	• Largely analogous to the present-day with lack of details about potential future changes in diurnal weather patterns [54] • Lack of future extreme weather conditions [54] • Potential difference in the reference timeframe of the GCM data and a chosen 'present day' typical weather file causing under- or overestimation of climate change impacts [55] • Lack of physical consistency between climate variables due to the independent 'morphing' of climate variables. It creates a different relationship between the variables to that currently observed at the site [56]
Statistical downscaling using stochastic methods	• Is possible to simulate extreme weather conditions that have not yet been observed, while being statistically representative for the location [7] • Is possible to simulate a wide range of feasible climate conditions [7]	• Relies on statistics derived from historical observations of climate [57] • There is an inherent assumption that future weather patterns will be the same as those observed historically [7] • This method has difficulties in modeling with accuracy some of the climatic variables [58]

All the above mentioned methods are capable of providing high resolution weather data for several years into the future. Weather data in a BPS readable format (e.g., EPW format) is required. Experts achieve this by following the principles used for creating Typical Meteorological Year (TMY) [21]. This method selects twelve typical meteorological months from the basis years to create TMY. The conventional period for the basis years is 30 years, as defined by the World Meteorological Organization (WMO) [59]. In the following section, the approaches that follow the above methods plus some approaches for generating extreme weather years are introduced briefly. All of these approaches are used in this study.

2.2 Generating future weather files ready to use in BPS

2.2.1 Typical future weather data sets

Hall et al. [21] in 1978 developed a method for creating TMY, which is one the most commonly used methods for creating typical weather years. The method selects the most representative month from several years of observed data for a location, for each of the twelve months of a year, based on Finkelstein–Schafer (FS) statistics. It then combines these into one year that is called TMY. It relies on statistical measures of the similarity of the distributions of daily indices such as minimum, mean, and maximum for four climate variables: dry-bulb temperature, dew-point temperature, wind speed and solar radiation [33].

As mentioned before, it is common to use the TMY method to create future typical weather data sets from many years of GCM or RCM generated data. The advantage of using TMY is a decrease in the calculation load (one year represents 30 years) whilst the most representative conditions are taken into account. However, the main disadvantage is neglecting (or underestimating) extreme weather conditions because of the averaging nature of the process [46]. The increasing recognition of climate change, that not only includes changes in average conditions, but also weather extremes [60], also means events such as hurricanes, heat waves and cold snaps will be more frequent and stronger. This phenomena has been studied at several locations around globe including Australia [61], Russia [62], UK [63] and south-east Europe [64]. Existing and new buildings will therefore face more extreme conditions more frequently and at higher intensities than those used to inform their design. As a result, designers should be equipped with methods that allow them to test their design even under extreme conditions.

2.2.2 Future weather data sets taking account of extreme conditions

As previously discussed, buildings should be assessed for more frequent and stronger future extreme weather conditions [65]. It is therefore important to take into consideration these extremes, even from the early design stage. The averaging process in creating TMY files based on 20-30 years of historical data or of future generated weather data, results in a mild year that usually excludes extreme values. Several researchers have suggested using extreme weather data sets rather than just one typical set in building simulations, to ensure that extremes and the probable impacts of climate change are not underestimated. For example, Crawley et al. [3] propose the use of more than one weather file in building simulation. They began, in their study, with four combinations of extremes to create Extreme Meteorological Year (XMY): daily maximum, daily minimum, hourly maximum, hourly minimum for an initial set of variables of dry-bulb temperature, dew-point temperature, solar insolation, precipitation, relative humidity, and wind speed. They used two approaches to select the extreme months. Firstly they looked at the daily maximum and minimum values for each day of the month and selected the month with the highest daily maximum value and the lowest daily minimum. Secondly they looked at the average hourly value for the month and selected the months with the highest hourly and lowest hourly average value. Using prototype building models, they concluded that XMY based on hourly maximum and minimum dry-bulb temperature best captured the range of energy use for the XMY. They suggest that BPS users should use three weather files, one TMY and two XMYs based on hourly maximum and minimum dry-bulb temperature to induce a range of building energy performance.

Another method for generating future weather files that can represent typical and extreme weather conditions was proposed by Nik [46]. The method is based on synthesizing one typical and two extreme (cold and warm) data sets: Typical Downscaled Year (TDY), Extreme Cold Year (ECY) and Extreme Warm Year (EWY). The process for creating a TDY starts by following the method for creating a TMY file, except that just one climate variable (dry-bulb temperature) is considered in the selection of typical months instead of four. There are different reasons for this, which includes the difficulties and uncertainties in weighting the climatic variables, as climate change does not equally affect all climate variables (refer to [46] for additional details). A similar procedure is used to create ECY and EWY data sets. However, instead of looking for the least absolute difference, the years with the maximum (for ECY) and minimum (for EWY) absolute difference are selected as the years representing the extreme temperatures for each month. Nik showed that by using the three data sets and considering TDY, ECY and EWY together (which is called Triple), it is possible to achieve a probability distribution of future conditions which is very similar to the full set of 30 years RCM data.

It was mentioned in Section 2.1.1 that it is necessary to consider several climate scenarios instead of just one scenario in the impact assessment on buildings, due to significant uncertainties in climate modeling. The method developed by Nik [46] was also used to overcome the challenge of climate uncertainties, the method synthesizing one set of representative weather files that takes into consideration several climate scenarios (e.g. in [46], five climate scenarios were considered – i.e. 5×30 years of data for a 30-year time span – and TDY, ECY and EWY were synthesized). This allows an impact assessment to be performed under both typical and extreme conditions with a minimum number of required simulation runs and in which climate uncertainty is taken into account.

3 Methodology

A set of 74 weather files were generated to compare the different approaches used in future climate projection. These combine all the available approaches drafted in Figure 2 for three different future time ranges, as described in detail in Section 3.1.5. The city of Geneva, Switzerland was used in this study as a reference location to generate and compare different future weather data sets using these methods. All data were formatted into the EPW weather file format.

16 reference commercial building models, as proposed by the ASHRAE standard 90.1 [66], were simulated using EnergyPlus [67] to assess the impacts of the typology of future weather data sets on building energy simulations. The buildings cover a wide range of types, from small office buildings to large energy intensive buildings such as hospitals, building models being described in Section 3.2.1. The 16 building models were furthermore used to build a virtual neighborhood in the city of Geneva, to observe the impact at the neighborhood scale. The neighborhood contains the same building typology split as the canton of Geneva (see Section 3.2.2).

3.1 Future weather data for Geneva

The weather data sets that are used in this work were generated using three future weather generator tools (CCWorldWeatherGen, WeatherShift™, and Meteonorm) and one RCM (RCA4, the 4th generation of the Rossby Centre Regional Atmospheric Climate Model [68]). RCA4 data, downscaling four different GCMs, was used in this work.

3.1.1 The CCWorldWeatherGen tool

Jentsch et al. [55] in 2013 provided a methodology for generating future weather data for different locations around the world. They chose the output data of the HadCM3 [69], forced with IPCC A2 emission scenario and applied the morphing method to generate EPW files. The HadCM3 A2 data provided by the IPCC data distribution center (DDC) [70] simulated monthly values of relative changes in climate between the 1961-1990 baseline climate and three future time slices, the 2020s, 2050s and 2080s. They developed a Microsoft® Excel based tool called the *'Climate Change World Weather Generator',* commonly referred to as CCWorldWeatherGen. This tool superimposes relative change on the weather variables stored in an EPW file and is freely available. It allows the user to generate future weather files for worldwide locations within three time slices: 2011-2040 (referred as '2020s'), 2041-2070 (referred as '2050s') and 2071-2100 (referred as '2080s'). It transforms an original EPW typical weather file into future weather data, formatted in the EPW format and so ready for use in BPS tools. Jentsch describes in detail the potential source of inaccuracy in the outputs of the tool due to the possible difference in the reference timeframe between HadCM3 and the EPW data [55]. For example, in this study the original TMY file is an IWEC (International Weather for Energy Calculations) data file for Geneva, derived from observations collected in the period 1982-1999. As mentioned before, the HadCM3 A2 data are relative changes in relation to the 1961-1990 baseline climate. Applying CCWorldWeatherGen to the IWEC weather file will superimpose the relative changes from the 1961-1990 baseline on to the data from 1982-1999. The latter period has higher temperature levels than the 1961-1990 baseline. An overestimation of results in the morphed data set is therefore expected. More details on the generation of climate variables for future weather data are available in [54], [47].

3.1.2 WeatherShift™ tool

Arup and Argos Analytics consulting firms developed a tool named *WeatherShift*™ [71], [72] based on the RCP4.5 and RCP8.5 emission scenarios of the IPCC Fifth Assessment Report (AR5). This applies the morphing method on to the outcomes of 14 GCMs (out of approximately 40 models) available under AR5 [19]. The tool provides future projection weather data for three time periods: 2026-2045 (referred as '2035s'), 2056-2075 (referred as '2065s'), 2081-2100 (referred as '2090s'). These are relative to the baseline climate of 1976-2005 and under the two emission scenarios. WeatherShift™ moreover provides a cumulative distribution function (CDF) that is constructed for each variable using linear interpolation between the model values [71]. This method was introduced earlier from the UK Climate Impact Programme (UKCIP) for the UK Climate Projections [73]. The CDF enables users to assign a probability to the projections, a sort of 'warming percentile'. For the purpose of this study, the 50th percentile and the RCP 8.5 emission scenario were chosen for setting the tool to generate future weather data sets base on the IWEC weather file of Geneva for the three available time periods.

3.1.3 Meteonorm

This tool is a combination of climate database, spatial interpolation tool and a stochastic weather generator. Meteonorm can calculate typical years with hourly resolution for any site and can also be used for climate change studies. This tool uses the GCMs under the IPCC fourth assessment report (AR4) rather than climate data stored in typical weather files. It can generate future weather files in different formats and according to different IPCC emission scenarios (B1, A1B and A2) for 10-year bins between 2010 and 2100 [57]. The Meteonorm version 7.2 was used in this study to generate a typical weather file and three future weather files for the A2 emission scenario and for the years 2020, 2050 and 2080 for the city of Geneva.

3.1.4 TDY, ECY and EWY out of RCA4

Part of the data from Nik's work [46] is used in this study and transformed into EPW format. The Rossby Centre Regional Atmospheric Climate Model (RCA4) [68] is used to dynamically downscale weather data from four GCMs (Table 2) to the spatial resolution of 12.5 km^2 and the hourly temporal resolution.

Table 2. The Global Climate Models (GCMs) used in the downscaling process by the Rossby Centre regional atmospheric climate model (RCA4).

Full name	Short name	Originating group	Model version
Centre National de Recherches Météorologiques	CNRM	CNRM/CERFACS, Toulouse, France	cnrm-cm5
Irish Centre for High-End Computing	ICHEC	EC-Earth Consortium, Europe	ec-earth

Institut Pierre Simon Laplace	IPSLm	IPSL, Paris, France	ipsl-cm5a-mr
Max Planck Institute for Meteorology	MPIM	MPIM, Hamburg, Germany	mpi-esm-lr

The adopted greenhouse gas concentration trajectories are RCP8.5 and RCP4.5 for CNRM and ICHEC, and RCP8.5 for IPSLm and MPIM. This gives an ensemble of six GCM-RCM combinations. RCA4 outputs were used to synthesize TDY, ECY and EWY for three future time periods, 2010-2039, 2040-2069 and 2070-2099. This generated six sets of representative weather data sets (each containing TDY, ECY and EWY) for each time period, resulting in a total of 54 weather files. One group of representative weather data (containing typical and extreme cold and warm) was, furthermore, synthesized by considering all the six climate scenarios at each time period (resulting in a total of nine weather files for three time periods). These files are henceforth called "Multi-Scenario" weather files (referring to the consideration of multiple climate scenarios). The three representative files in this group are named $TDY_{Multiple}$, $ECY_{Multiple}$ and $EWY_{Multiple.}$ For more details, refer to [46].

3.1.5 Generated future weather data sets

Each of the aforementioned methods provide future weather files for slightly different time slices. In the interests of harmonization, three future projected periods namely near-term (NT), medium-term (MT) and long-term (LT) were adopted. The expressions 'Near-Term' and 'Long-Term' are used in chapters 11 [74] and 12 [75] of IPCC AR5 to refer to the time periods 2016-2035 and 2081-2100 respectively. The term 'Medium-Term' is introduced in this work and follows the same logic. Table 3 shows the alignment of the original output periods of the files to the three identified time slices.

Table 3. Adopted terms for the variety of time slices used by the different methods or tools.

Adopted Term	CCWorldWeatherGen	WeatherShift™	Meteonorm	RCA4
Near-term	2011-2040	2026-2045	2011-2030	2010-2039
Medium-term	2041-2070	2056-2075	2046-2065	2040-2069
Long-term	2071-2100	2081-2100	2080-2099	2070-2099

Weather files were grouped into two categories to distinguish between different generated future weather data. These were: *typical weather data sets* and *extreme weather data sets.* They include weather files from statistical and dynamical data groups as shown in Figure 3.

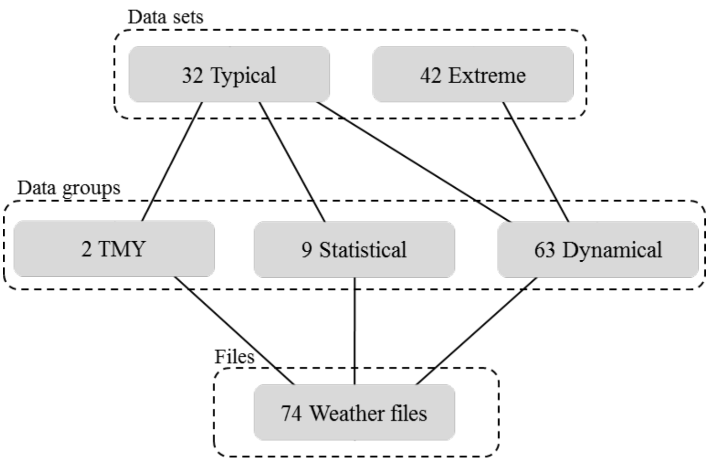

Figure 3. Weather files are grouped into two categories: typical weather data sets and extreme weather data sets, which include weather files from statistical and dynamical data groups.

The data sets are grouped into three data groups:

- TMY data group: includes two weather files, the IWEC typical meteorological year (TMY) and a TMY generated by Meteonorm,
- Statistical data group: six weather files generated using the morphing method through CCWorldWeatherGen and WeatherShift, and three weather files generated using the stochastic method through Meteonorm,
- Dynamical data group: 21 weather files generated using dynamical downscaling that represent typical conditions and 42 weather files generated using dynamical downscaling that represent extreme conditions.

Typical weather data sets refer to the files that are generated through statistical downscaling or dynamical downscaling (TDY series). Extreme weather data sets refer to ECY and EWY files that represent extreme cold and warm years (using the RCM dynamically downscaled data). All the above methods provide 72 future weather files for the city of Geneva as shown in Table 4. A total of 74 files were used in this study, including two TMY weather files.

Table 4. Weather files generated for the city of Geneva and used in this study.

Method	Tool/GCM/RCM	Emission scenario	Number of weather files	Adopted term
Statistical	CCWorldWeatherGen	A2	3*	CCW_a2
	WeatherShift	RCP 8.5	3	WSH_rcp85
	Meteonorm	A2	3	MTN_a2
Dynamical-typical	MPIM-RCA4	RCP 8.5	3	MPIM_TDY_rcp85
	IPSLm-RCA4	RCP 8.5	3	IPSLm_TDY_rcp85
	ICHEC-RCA4	RCP 8.5, RCP 4.5	3×2	ICHEC_TDY_rcp85 ICHEC_TDY_rcp45
	CNRM-RCA4	RCP 8.5, RCP 4.5	3×2	CNRM_TDY_rcp85 CNRM_TDY_rcp45
	Multi GCMs-RCA4	RCP 8.5+RCP 4.5	3	$TDY_{Multiple}$
Dynamical-extreme	MPIM_RCA4	RCP 8.5	3×2	MPIM_ECY_rcp85 MPIM_EWY_rcp85
	IPSLm_RCA4	RCP 8.5	3×2	IPSLm_ECY_rcp85 IPSLm_EWY_rcp85
	CNRM_RCA4	RCP 8.5, RCP 4.5	3×4	CNRM_ECY_rcp85 CNRM_EWY_rcp85 CNRM_ECY_rcp45 CNRM_EWY_rcp45
	ICHEC_RCA4	RCP 8.5, RCP 4.5	3×4	ICHEC_ECY_rcp85 ICHEC_EWY_rcp85 ICHEC_ECY_rcp45 ICHEC_EWY_rcp45
	Multi GCMs_RCA4	RCP 8.5+RCP 4.5	3×2	$ECY_{Multiple}$ $EWY_{Multiple}$

* refers to three time periods; one weather file for each period.

A2, RCP8.5 and RCP4.5 are the three future emission scenarios present in the above list of weather files. According to IPCC fifth assessment synthesis report [76]: RCP8.5 scenario is broadly comparable to A2 scenario and both describe very high GHG emissions, and RCP4.5 is an intermediate scenario. The report further describes: "*Relative to 1850–1900, global surface temperature change for the end of the 21st century (2081–2100) is projected to likely exceed 1.5°C for RCP4.5 and RCP8.5 (high confidence). Warming is likely to exceed 2°C for RCP8.5 (high confidence), more likely than not to exceed 2°C for RCP4.5 (medium confidence)*". The above weather data sets allow considering the uncertainty of climate projections into energy calculations. The span of values resulted from simulations under these weather files, shows the uncertainty of buildings energy performances in future following IPCC emission scenarios, and hence offer the opportunity to test a building under the wide-expected range of climate uncertainty.

3.2 Simulation test bench

3.2.1 Building models

The ASHRAE standard 90.1 suite of commercial reference building models was chosen to be used in this study [77] to assess the impact of climate change on the energy performance of buildings. The commercial reference building models were developed by Pacific Northwest National Laboratory (PNNL), under contract with the U.S. Department of Energy (DOE). These building models were originally derived from DOE's Commercial Reference Building Models with modifications from the ASHRAE 90.1 committee, Advanced Energy Design Guide series, and other building industry expert input. Detailed descriptions of the reference model development and modeling strategies can be found in PNNL's reports [78], [79]. The building models used in this study are complying with ASHRAE 90.1-2013 standard. The suite is a collection of standardized building models with realistic building characteristics and includes 16 buildings of different types and dimensions (Figure *4*). The suite provides a simulation bench test to compare the relative impact of using the generated weather files (in section 3.1) on energy performance of various building types. Technical descriptions of the selected building envelope components, used in building models, are given in Table 5.

Table 5. Technical description of building envelope components of reference building models.

Building Type		U-value (W/(m²K))									SHGC	
		Roof			External Wall				Glazing		Glazing	
		I	II	III	I	II	III	IV	Windows	Skylight	Windows	Skylight
Apartment	High-rise	0.18	-	-	0.36	-	-	-	0.42	-	0.40	-
	Mid-rise	0.18	-	-	0.36	-	-	-	0.42	-	0.40	-
Hotel	Large	0.18	-	-	-	0.51	0.59	-	0.42	-	0.40	-
	Small	0.18	-	-	0.36	-	-	-	0.42	-	0.40	-
Office	Large	0.18	-	-	-	-	0.59	-	0.42	-	0.40	-
	Medium	0.18	-	-	0.36	-	-	-	0.42	-	0.40	-
	Small	-	0.15	-	0.36	-	-	-	0.42	-	0.40	-
Health	Hospital	0.18	-	-	-	0.51	0.59	-	0.42	-	0.40	-
	Outpatient	0.18	-	-	0.36	-	-	-	0.42	-	0.40	-
Restaurant	Fast-food	-	0.15	-	0.36	-	-	-	0.42	-	0.40	-
	sit-down	-	0.15	-	0.36	-	-	-	0.42	-	0.40	-
Retail	Standalone	0.18	-	-	-	-	0.59	-	0.42	0.75	0.40	0.6
	Strip Mall	0.18	-	-	0.36	-	-	-	0.42	-	0.40	-
School	Primary	0.18	-	-	0.36	-	-	-	0.42	0.75	0.40	0.6
	Secondary	0.18	-	-	0.36	-	-	-	0.42	0.75	0.40	0.6
Warehouse	Warehouse	-	-	0.20	-	-	-	0.30	0.42	0.75	0.40	0.6

ASHRAE 90.1 [66] defines U-factor (U-value) as: "*heat transmission in unit time through unit area of material or construction induced by a unit temperature difference between the environments on each side.*" and defines solar heat gain coefficient (SHGC) as: "*The ratio of the solar heat gain entering the space through the fenestration area to the incident solar radiation.*"U-value and SHGC of glazing in Table 5 are independent of frame material. Roof U-value of the prototype buildings varies between 0.15 to 0.20 W/(m^{2}K) depending on the

roof type. Wall U-value varies from 0.30 to 0.59 W/(m^2K) depending on the wall type. For more details, please refer to PNNL's technical report [80].

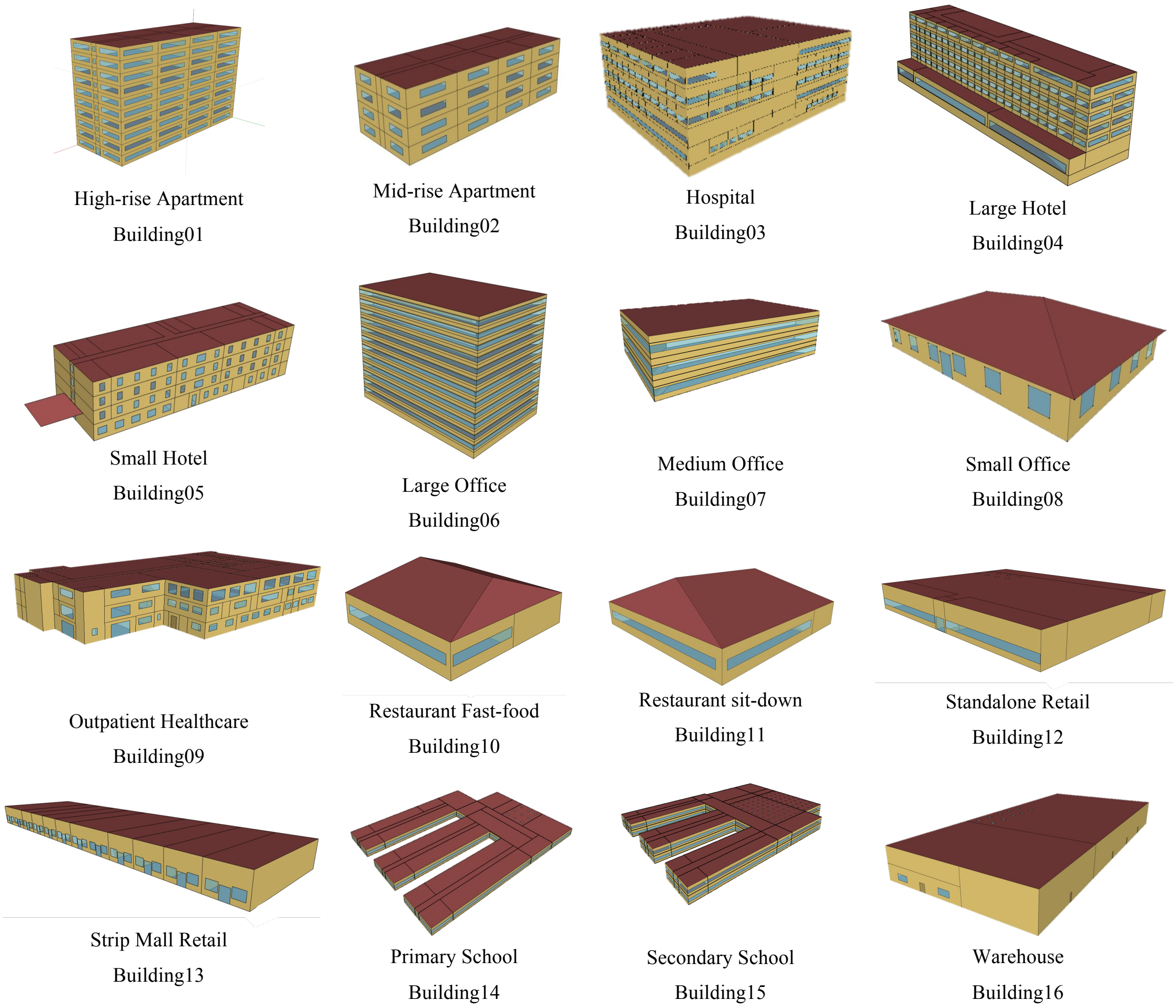

Figure 4. Reference building models from the ASHRAE Standard 90.1. The total area of these building models and the number of their conditioned zones are presented in Table 6.

3.2.2 Virtual neighborhood of Geneva

A combination of the 16 buildings was used to virtually model a neighborhood. We looked at the neighborhood of Champel in Geneva to get an idea of the scale of such a neighborhood, which has a total building area of 328 105 m^2 [81]. The distribution of the areas occupied by the buildings in the canton of Geneva was used to distribute the 16 buildings based on type. In the canton, 64 % of buildings are residential and 36 % are non-residential and mixed-use buildings [82]. The above assumptions gave the virtual neighborhood created for this study, which had a total energy reference area of 414 341 m^2, 64.3 % residential buildings and 35.7 % non-residential buildings. The composition of the virtual neighborhood is presented in Table 6. This composition was used only to assess the magnitude of impacts at the neighborhood scale. The spatial attributes of a neighborhood (organization of the buildings and infrastructure between) are not within the scope of this paper.

Table 6. Composition of the 16 ASHRAE standard 90.1 reference buildings in the virtual neighborhood for city of Geneva.

Building number	Name	floor Area of Thermally conditioned space (1) (m^2)	Number of floors	Number of thermal zones (2)	Windows-to-wall ratio (3)	Number of building type in the neighborhood (4)	Percentage of floor area in the whole neighborhood (5)
Building01	High-rise apartment	7059.9	10	80	30%	20	37.8 %
Building02	Mid-rise apartment	2824.0	4	32	20%	35	26.5 %
Building03	Hospital	22436.2	5	162	16%	1	5.4 %
Building04	Large hotel	10736.3	6	195	30.2%	1	2.6 %
Building05	Small hotel	3725.1	4	54	10.9%	2	1.9 %
Building06	Large office	46320.4	12	74	37.5%	1	11.2 %
Building07	Medium office	4982.2	3	18	33%	3	3.6 %
Building08	Small office	511.0	1	6	20.1%	5	0.6 %
Building09	Outpatient healthcare	3804.0	3	118	20%	1	0.9 %
Building10	Restaurant fast-food	232.3	1	2	14%	8	0.4 %
Building11	Restaurant sit-down	511.2	1	2	17.1%	3	0.4 %
Building12	Standalone retail	2294.0	1	5	7.1%	1	0.6 %
Building13	Strip mall retail	2090.3	1	10	10.5%	1	0.5 %
Building14	Primary school	6871.0	1	25	35%	1	1.7 %
Building15	Secondary school	19592.0	2	46	33%	1	4.7 %
Building16	Warehouse	4835.1	1	3	0.7%	1	1.2 %

(1) Defined by ISO 52000-1:2017 [83] as: heated and/or cooled space.

(2) Number of thermal zones in the energy model.

(3) Defined by ASHRAE 90.1 [66] as: The ratio of vertical fenestration areas to the gross above-grade wall area.

(4) Number of each building type in the virtual neighborhood.

(5) Percentage of each building type in the total floor area of the neighborhood.

3.2.3 Simulation workflow

A simulation workflow was implemented in the multidisciplinary design optimization platform modeFRONTIER [84] coupled with MATLAB for post-processing of the output data. This was used to simulate the full set of 16 building models under the 74 generated future weather files, giving a total of 1 184 simulation runs. modeFRONTIER used the algorithm presented in Figure 5 to perform the simulations.

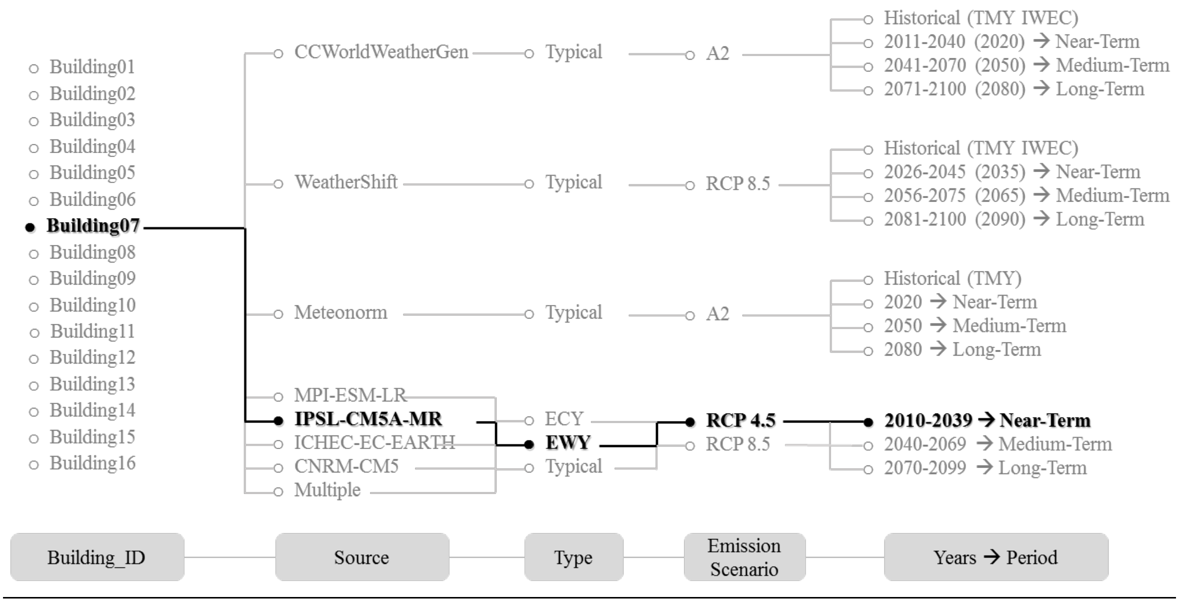

Figure 5. Configuration of simulation runs of 16 reference buildings under the generated future weather files. Simulation of building number 07, Medium Office, using weather file 'IPSL_EWY_rcp45_NT.epw' is highlighted as an example.

The dynamic energy simulations of the building models were performed using the software EnergyPlus [67] version 8.5.0. Each released version of EnergyPlus undergoes two major types of validation tests [85]: analytical tests according to ASHRAE Research Projects 865 and 1052, and comparative tests according to ANSI/ASHRAE 140 [86] and IEA SHC Task34/Annex43 BESTest method. Heat conduction through the opaque envelope was calculated via the conduction transfer functions (CTF) with a 15-minute time step. The natural convection heat exchange near internal and external surfaces was calculated using the thermal analysis research program (TARP) algorithm [87]. The initialization period of simulation was set to the maximum option, which is 25 days [88].

The output parameters that were obtained from EnergyPlus were delivered energy for space heating and cooling, and delivered energy for total electricity including electricity for heating, cooling, lighting, fans, domestic hot water and appliances. Delivered energy is defined in the ISO 52000-1:2017 standard [83] as: "energy, expressed per energy carrier, supplied to the technical building systems through the system boundary, to satisfy the uses taken into account (heating, cooling, ventilation, domestic hot water, lighting, appliances, etc.) or to produce electricity"

In the next step, delivered energy is converted to primary energy which is defined by the standard [83] as: "energy that has not been subjected to any conversion or transformation process".

Using primary energy allows comparisons of the energy performance of several building types that use different technical building systems supplied by different energy carriers. The primary energy conversion factors stipulated in Swiss norm SIA 380/1:2009 [89] were used. According to this standard, the factor for converting electricity to primary energy is 2.97 kWh_{PE}/kWh_{el} and for converting natural gas to primary energy is 1.15 kWh_{PE}/kWh_{gas}.

4 Results and discussion

The analysis uses graphical comparisons and statistical metrics to characterize the differences between the future weather projections generated using statistical and dynamical downscaling methods. For the sake of harmonization, all the graphs in this section use the color black for the TMY data group, green for the statistical data group, blue for typical weather files (TDY series) and red for extreme weather files (ECY and EWY series) of the dynamical data group. This section firstly presents the distributions of values for hourly dry-bulb temperature in all the weather files. Then the impacts of future weather data type on the energy simulation of buildings are assessed using just typical weather data sets. The final part of the results focuses on the importance of considering extreme conditions in designing buildings and energy systems for buildings.

4.1 Comparison of generated weather files

Each EPW weather file contains the hourly values for an entire year for a number of weather variables, e.g. dry-bulb temperature, dew-point temperature, direct and diffuse solar radiation, wind speed, and wind direction. All the generated files that were used in this study contained information on the effect of climate change on at least the following climate variables:

- Dry Bulb Temperature
- Dew Point Temperature
- Relative Humidity
- Direct Normal Radiation
- Diffuse Horizontal Radiation
- Global Horizontal Radiation
- Wind Speed

All the above items are used directly in the EnergyPlus program, which means that the results reported in this study are already affected by changes to all these variables. Boxplots of the outdoor dry-bulb air temperature, which are one of the key variables in energy simulation [3], are plotted in Figure 6. The effect of climate change on different climate variables and the uncertainty of estimating these variables by climate models are discussed in previous works of the authors [14], [32], [46], [90]. See Annex B for boxplots of three other climate variables, global horizontal radiation, relative humidity and wind speed. There are boxplots for all the 74 weather files, all showing values for near-term (NT), medium-term (MT) and long-term (LT) periods. The distributions of the outdoor dry-bulb air temperature are compared with the distribution of maximum and minimum daily values for observed data for the period 1955-2017. These are used as a reference or control sample. Observed data are based on weather data from the Genève-Cointrin weather station obtained from National Centers for Environmental Information (NCEI) [91]. The brown dashed lines project lower and upper whiskers of daily minimum and daily maximum distributions of temperature and the brown horizontal dotted line marks the average daily temperature for the period of observed data.

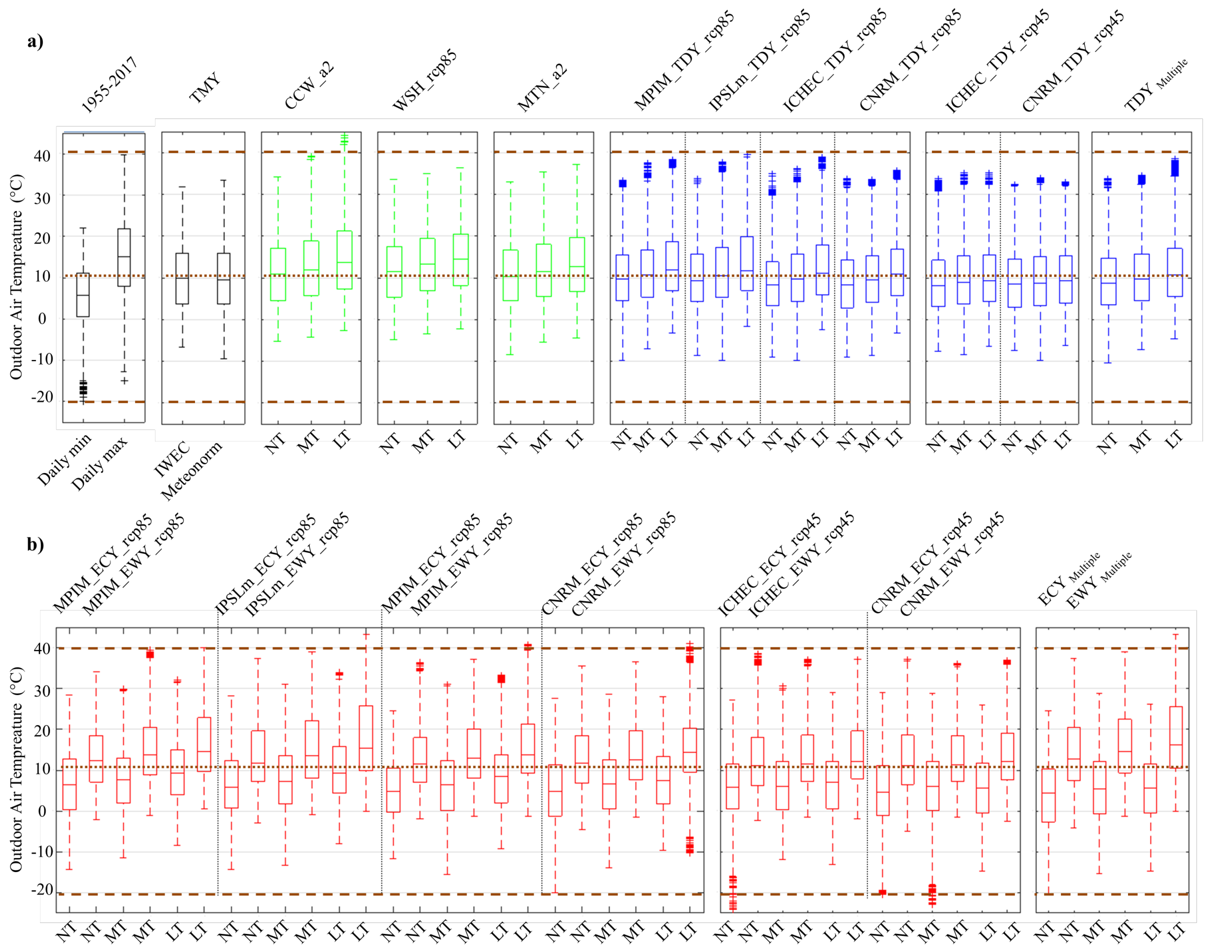

Figure 6. Boxplots of the outdoor dry-bulb air temperature for the weather files generated by three software tools–CCWorldWeatherGen, WeatherShiftTM, Meteonorm –and six combinations of GCM-RCMs with different emission scenarios. The dashed lines show the lower w whiskers for minimum daily temperature and the upper whiskers of the maximum daily temperature and the horizontal dotted brown lines show the average according to recorded data from 1955 to 2017 of Genève-Cointrin weather station. a) Historical observed data and typical weather data sets, b) extreme weather data sets.

Figure 6 shows a pattern of continuous increase in the average dry-bulb temperature from NT to MT and LT, and for all future weather files. The slope of increase is greater for weather files with A2 and RCP 8.5 emission scenarios than for RCP 4.5, which is in agreement with the GCM projections for these scenarios. An increasing trend exists for all generated weather files. However, the maximum values of typical future weather files only get close to the historical observed value of maximum temperature under LT. This reveals the weakness of typical weather files in representing extreme conditions, as is discussed in section 2.2.2. For extreme weather data sets, the distribution of EWY series for the RCP8.5 scenario is close to the observed maximum daily temperatures and the ECY series of RCP4.5 is close to the distribution of observed minimum daily temperatures. Using Multi-Scenario files therefore improves the coverage of both maximum and minimum borders of the distributions for dry-bulb temperature. These files approximately cover the distributions of all other dynamical data group files. This means that it is possible to reduce the number of simulations by using Multi-Scenario weather files instead of several weather files (six in this case) with different climate scenarios, as was shown in [46] and [90].

Climate change affects climate variables and their long-term and short-term variations. Statistical data group weather files are only able to capture information on the long-term changes that are provided by the original GCM outputs (with monthly time resolution). These types of files are generated under the assumption that short-term future weather patterns will follow the same pattern and climate variability as historical weather data. They therefore cannot represent probable future extreme conditions due to climate change. Conversely, the weather files of the dynamical data group are not constrained by historical data. To better illustrate the difference between the two types of weather data, the hourly outdoor dry-bulb temperature for one day (1st February as an example) is plotted in Figure 7 for statistical data group weather files and one dynamical data group weather file under NT, and compared with TMY IWEC.

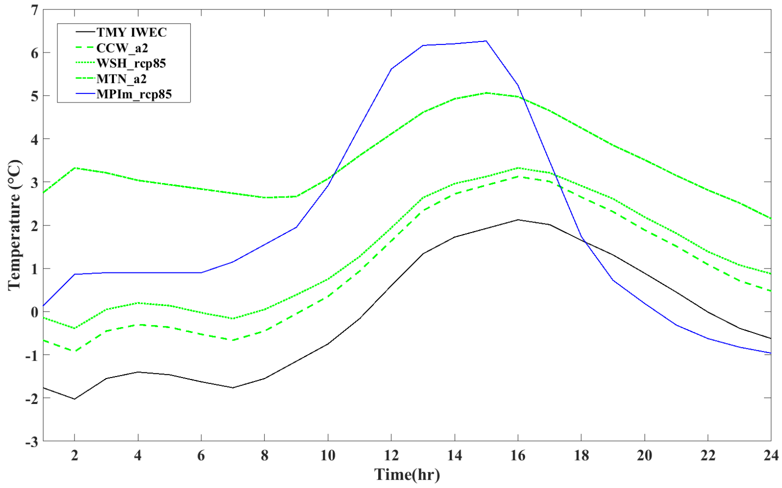

Figure 7. Hourly outdoor dry-bulb temperature for one day (1st February as an example) are plotted for three weather files of statistical group (in green) and one weather file of the dynamical group (in blue) under NT and compared to TMY IWEC (in black).

As expected, the hourly temperature profiles of the CCW_a2, WSH_rcp85 and MTN_a2 future weather files in Figure 7, the statistically downscaled type, have a very similar pattern to the TMY IWEC file with a higher average temperature. The MPIm_rcp85 dynamical group file does not, however, match the other profiles. This again points to the fact that weather files generated using statistical methods cannot represent short-term variations of climate conditions induced by climate change.

The annual and seasonal averages for dry-bulb temperature and their monthly variations are compared in Table 7 for 14 cases to investigate the long-term changes of average values and variations of climate variables. The 14 cases are: 30 years of observed data (1961-1990), 12 typical weather files (TMY data group, the statistical data group and TDY series of the dynamical data group) and "Triple$_{Multiple}$" which is the average of values for TDY$_{Multiple}$, ECY$_{Multiple}$ and EWY$_{Multiple}$, all under LT. The meteorological seasons were defined by Palatine Meteorological Society (1780) as periods of three months: winter starting on 1st December, spring on 1st March, summer 1st June and autumn on 1st September [92]. The absolute difference between weather files and the observed data is shown in Table 7 under "Absolute change to the baseline period 1961-1990", to help us better understand the differences between the weather files and the observed data.

Table 7. Annual and seasonal averages of outdoor temperature (°C) under LT for typical weather data sets and TripleMultiple (the average of values for TDYMultiple, ECYMultiple and EWYMultiple) and their absolute difference to the values of baseline observed period (1961-1990).

		Mean of monthly values (°C)					Absolute change to the baseline period 1961-1990 (°C)				
		Annual	Seasonal				Annual	Seasonal			
Period	Type		Spring	Summer	Autumn	Winter		Spring	Summer	Autumn	Winter
1961-1990	Observed data	9.6	9.0	17.9	10.1	1.5	0.0	0.0	0.0	0.0	0.0
1982-1999	TMY IWEC	10.4	9.8	18.9	10.3	2.4	0.7	0.8	1.1	0.2	0.9
1961-1990	TMY Meteonorm	9.8	9.1	18.2	10.2	1.8	0.2	0.1	0.4	0.1	0.3
2071-2100 (LT)	CCW_a2	14.9	13.3	25.2	15.1	5.8	5.2	4.3	7.4	5.0	4.3
2081-2100 (LT)	WSH_rcp85	14.8	14.1	23.5	15.2	6.6	5.2	5.1	5.6	5.1	5.1
2080-2099 (LT)	MTN_a2	13.3	11.9	22.7	13.8	4.6	3.6	2.9	4.8	3.7	3.2
2070-2099 (LT)	MPI _rcp85	13.0	11.0	22.5	13.0	5.5	3.4	2.0	4.6	2.9	4.0
	IPSL _rcp85	13.6	10.4	23.3	14.6	5.9	3.9	1.4	5.5	4.5	4.4
	ICHEC _rcp85	12.2	9.8	21.7	12.7	4.5	2.6	0.8	3.9	2.6	3.0
	CNRM _rcp85	11.6	9.5	20.2	12.1	4.5	1.9	0.4	2.3	2.0	3.0
	ICHEC _rcp45	10.2	8.5	18.8	10.6	2.8	0.5	-0.5	0.9	0.5	1.4
	CNRM _rcp45	9.8	7.9	18.3	10.3	3.0	0.2	-1.2	0.4	0.2	1.5
	$TDY_{Multiple}$	11.6	9.5	20.7	12.0	4.3	2.0	0.5	2.9	1.9	2.8
	$Triple_{Multiple}$	11.7	9.9	21.7	12.2	3.1	2.1	0.8	3.8	2.1	1.6

The annual average temperature shows an increase for all future weather files under LT of between 0.2 to 5.2 °C in relation to the 1960-1991 baseline period. It can be highlighted that values of TMY IWEC also show an increase in annual average temperature. This can be the reason for relatively higher values of CCWorldWeatherGen and WeatherShift outputs, as discussed in section 3.1.1. The range of values for different scenarios highlights the importance of considering several scenarios for climate change impact assessment, as emphasized by IPCC [93] and other studies (e.g., [94]).

It is also interesting to see the seasonal variations in the weather files. Table 7 shows that the highest increase of temperature in relation to the baseline for weather files and with A2 and RCP8.5 emission scenarios is in summer (except for CNRM_rcp85). Interestingly, the highest increase for weather files with RCP4.5 scenarios occurs in winter. Another notable result for RCP4.5 weather files is the decrease in temperature during spring.

$TDY_{Multiple}$ is generated to represent all the six climate scenarios in the dynamical data group. The values of annual and seasonal averages for this file are close to the mean of the other 6 scenarios. Comparing $TDY_{Multiple}$ with $Triple_{Multiple}$ shows that considering $TDY_{Multiple}$, $ECY_{Multiple}$ and $EWY_{Multiple}$ together ($Triple_{Multiple}$) results in higher values of annual and seasonal averages rather when considering $TDY_{Multiple}$ alone. Furthermore, these values show that the $Triple_{Multiple}$ is more extreme, with warmer summers and colder winters than the $TDY_{Multiple}$.

4.2 Climate change impact assessment using only typical weather files

In this section, the hourly primary energy for space heating and cooling (defined in section 3.2.3) requirements per square meter for the 16 reference buildings are calculated for one year under typical weather data sets. Figure 8 shows the distribution of calculated values for all the buildings.

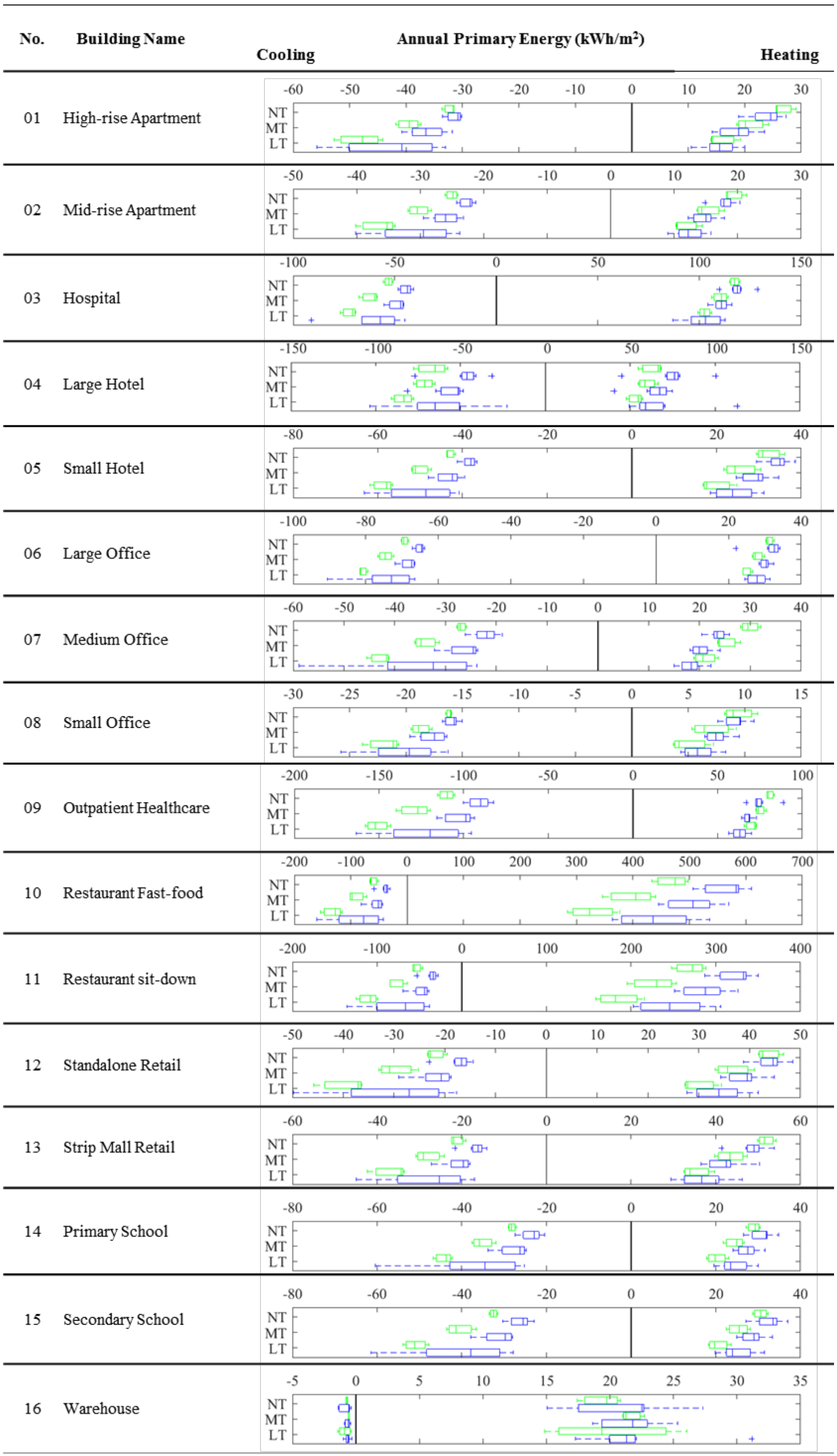

Figure 8. The boxplots present the distribution of values for the calculated annual primary cooling energy (negative values) and primary heating energy (positive values) under typical weather data sets for all 16 reference buildings. Values of the dynamical data group are presented in blue and the statistical data group in green.

The boxplots in Figure 8 for both statistical and dynamical under all NT, MT and LT of each building shows that the fast food restaurant has the largest range of primary energy. The range of values for this building is approximately 280-610 kWh/m^2/a for space heating and 30-160 kWh/m^2/a for space cooling. The reason for this can be the high ventilation rate of restaurant buildings compared to other buildings. The hospital has a relatively small range for primary energy for space heating (~ 85-130 kWh/m^2/a) and space cooling (~ 40-90 kWh/m^2/a). This is probably due to equipment energy use and other energy end-uses than heating, cooling and ventilation predominating in this building.

Overall, the shifting impact on primary cooling energy and primary heating energy is present for all buildings except building number 16 (warehouse). This might show that climate conditions are not the dominant force driving the energy performance of this building. A similar conclusion was proved for swimming facilities [95]. For some buildings, a heating-load dominated building under NT furthermore becomes a cooling-load dominated building under MT or LT. Examples of this are buildings number 14 and 15 (primary and secondary schools) as discussed by Pagliano et al. [96]. This reveals that both methods are able to provide enough information to show a shift in the energy use of the buildings.

The cumulative distribution of primary energy for heating and cooling for each building was calculated to show the impacts of weather data typology on energy calculations, for both hourly and annual values. As an example, Figure 9 presents these values for building number 7 (medium office) under NT, MT and LT periods.

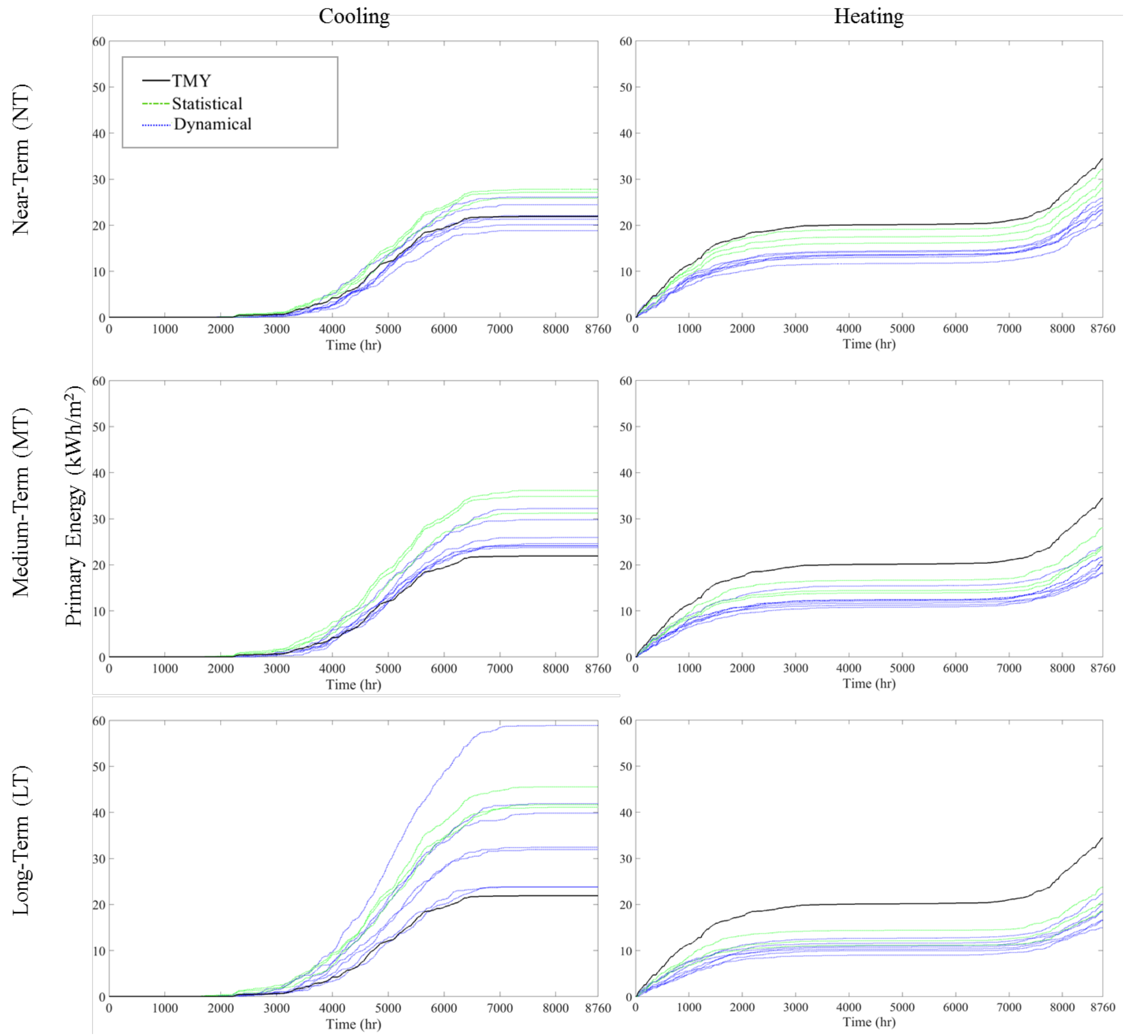

Figure 9. Cumulative distributions of primary cooling energy (on the left) and primary heating energy (on the right) for building07 (medium office) under typical weather data sets. Results of the dynamical data group are presented in blue color and the statistical data group in green.

Figure 9 shows that the overall primary energy for cooling for building07 (medium office) increases over time while the primary energy for heating tends to decrease moving from NT to LT. Furthermore, the uncertainty associated with calculating the building's primary energy using different weather files spreads consistently for space cooling but remains quite constant for space heating. The shape and variation of hourly values for cooling primary energy and heating primary energy are very similar for the statistical data group and the TMY IWEC file. This limitation of using the statistically downscaled method for discussing short-term variations has been previously discussed in the first part of the results, Figure 7 demonstrating that the hourly outdoor temperature profiles of the statistical group have the same pattern as the TMY IWEC file.

The extent of uncertainty for calculating primary energy presented in Figure 8 and Figure 9 substantiate previous proposals in the literature to prefer the probabilistic approaches for predicting building performance in the future [97] rather than the deterministic ones.

Total primary energy for space air conditioning, which is the sum of both the primary energy for cooling and heating, was calculated for all buildings under future typical weather data sets. *Table 8* provides the mean, median, minimum (min), maximum (max), range, and standard deviation (StDev) values for total annual primary energy and compares these values for the statistical and the dynamical data group.

Table 8. Descriptive statistics of the total annual primary energy for heating and cooling of all 16 reference buildings calculated under typical weather data sets for the statistical data group (9 weather files) and the dynamical data group (21 weather files).

No.	Building name	Downscaling method	Total annual primary energy for space conditioning (kWh/m^2)					
			Mean	**Median**	**Min**	**Max**	**Range=Max-Min**	**StDev**
01	High-rise Apartment	Statistical	61.2	60.6	57.4	67.0	9.6	3.65
		Dynamical	56.2	55.3	51.2	69.4	18.2	4.477
02	Mid-rise Apartment	Statistical	46.0	45.5	43.2	50.5	7.3	2.522
		Dynamical	41.5	41.1	38.7	51.5	12.8	2.943
03	Hospital	Statistical	172.5	171.6	169.9	176.8	6.9	2.593
		Dynamical	161.8	160.5	155.2	178.2	23	5.65
04	Large Hotel	Statistical	132.1	131.4	125.5	140.6	15.1	5.7
		Dynamical	129.0	125.1	117.3	158.5	41.2	11.09
05	Small Hotel	Statistical	76.5	75.6	73.1	81.3	8.2	2.812
		Dynamical	73.4	72.8	70.1	85.7	15.6	3.273
06	Large Office	Statistical	102.9	102.2	100.3	106.1	5.8	2.279
		Dynamical	99.2	98.0	88.2	116.2	28	4.87
07	Medium Office	Statistical	59.9	59.2	55.1	64.8	9.7	3.26
		Dynamical	48.9	47.1	42.7	75.5	32.8	7.27
08	Small Office	Statistical	26.1	26.0	24.2	28.4	4.2	1.641
		Dynamical	25.6	25.3	23.9	31.4	7.5	1.537
09	Outpatient Healthcare	Statistical	205.3	199.7	188.7	229.9	41.2	14.47
		Dynamical	174.6	167.3	155.6	220.1	64.5	16.24
10	Restaurant Fast-food	Statistical	492.5	499.6	411.4	549.3	137.9	43.4
		Dynamical	563.9	560.1	467.8	645.5	177.7	47.9
11	Restaurant sit-down	Statistical	307.7	314.9	266.3	334.4	68.1	21.88
		Dynamical	339.4	334.8	291.4	382.5	91.1	25.57
12	Standalone Retail	Statistical	67.2	66.2	64.2	73.5	9.3	3.2
		Dynamical	62.2	61.0	57.0	81.7	24.7	5.3
13	Strip Mall Retail	Statistical	72.2	73.3	66.8	76.2	9.4	2.907
		Dynamical	64.5	63.5	57.8	79.8	22	4.88
14	Primary School	Statistical	60.4	59.3	56.2	66.6	10.4	3.59
		Dynamical	57.3	55.2	52.5	83.9	31.4	6.82
15	Secondary School	Statistical	66.8	66.0	62.2	73.6	11.4	3.91
		Dynamical	61.8	59.8	57.4	85.4	28	6.42
16	Warehouse	Statistical	21.1	21.5	16.3	26.4	10.1	2.876
		Dynamical	22.2	22.3	16.2	31.5	15.3	3.327

Table 8 shows that the ranges of calculated annual primary energy demand for the dynamical group are significantly higher than corresponding values for the statistical data group. This can be due to the use of both low emission scenarios RCP4.5 and high emission scenario RCP8.5 in the dynamical data group. Sit-down and fast-food restaurants have, according to StDev values of primary energy in Table 8, the highest variation, which can and as mentioned before are probably due to the high ventilation rate for these buildings. Small office has the lowest variation, which can be due to a constant air volume ventilation system type for this building.

4.3 Climate change impact assessment using both typical and extreme weather files

It was mentioned in section 2.2.2 that, due to the averaging nature of the process for generating typical years, that this method is unable to provide information on extreme weather conditions. This problem can be illustrated by referring to the heat wave that hit Europe in the summer of 2003. The heat wave caused the death of thousands of elderly and vulnerable people, caused power cuts and many other damage [29]. Several studies have shown daily mortality during heat waves is highly correlated to maximum daily temperature and night temperature (e.g. in France [98], [99] and in Switzerland [27]). The Swiss Federal Office of Meteorology and Climatology (MeteoSwiss) provides climate indicators that characterize the climate, indicators such as hot days, frost days and tropical nights. These are also used to communicate how climate is changing. Hot days are defined as "days in which the temperature rises above 30 °C", frost days are defined as "days on which the temperature dips below 0 °C", and tropical nights are defined as "days on which the temperature does not dip below 20 °C". Table 9 shows the numbers of hot days and tropical nights during 92 days of summer in 2003 (1st June-31st August) for the city of Geneva. These values were compared to calculated values for the same period for two TMY weather files (IWEC and Meteonorm), two typical weather files under NT from statistical and dynamical groups (CCW_a2 and $TDY_{Multiple}$) and one extreme warm weather file ($EWY_{Multiple}$).

Table 9. Comparison of the number of hot days (Tmax ≥30°C) and tropical nights (Tmin ≥ 20°C) for the extremely hot summer of 2003 in Geneva calculated from different weather data sets.

		Number of hot days	**Number of tropical nights**
Observed data	Summer 2003*	51	4
TMY	IWEC	8	1
	Meteonorm	4	3
Near-Term (NT) future	CCW_a2	26	4
	$TDY_{Multiple}$	10	0
	$EWY_{Multiple}$	54	13

* based on meteorological data from Genève-Cointrin weather station provided by National Centers for Environmental Information (NCEI) [91].

It can be highlighted from Table 9 that only the $EWY_{Multiple}$ weather file value is comparable with the number of hot days that occurred during the summer of 2003 in Geneva. The TMY file and future typical weather file values are far from observed values. The above example reveals how the averaging process can result in missing extreme values and therefore shows how systems designed taking into consideration only typical conditions could quickly become a costly mistake (due to under-dimensioning). The 16 buildings models were simulated in this section under both typical and extreme weather data sets for the dynamical data group, to assess the impact of extreme conditions on the energy performance of buildings. Three sets of weather data were considered for the purpose of this analysis; $TDY_{Multiple}$, $ECY_{Multiple}$ and $EWY_{Multiple}$. These represent all six climate scenarios in the dynamical data group. Figure 10 represents the distribution of hourly energy demands taking into consideration (i) only $TDY_{Multiple}$ (8760 values), and (ii) all the three sets together, which is referred to as $Triple_{Multiple}$ (3×8760 values). Boxplots of hourly energy demand for cooling and heating are presented for the buildings and three time periods. This technique allows us to investigate the impact of taking into consideration extreme conditions on the distribution of heating and cooling demands for each building.

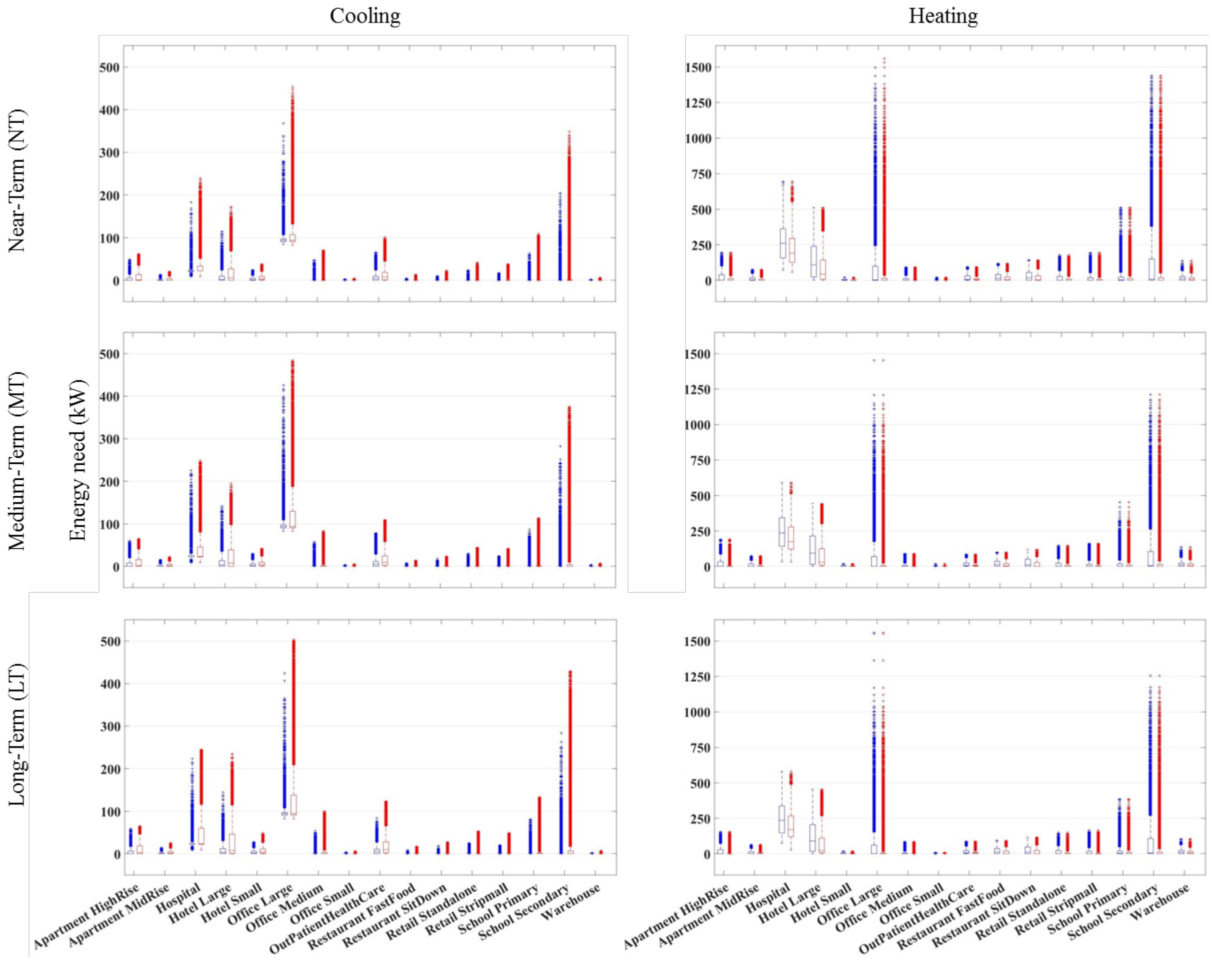

Figure 10. Boxplot of hourly cooling demand and heating demand for all 16 reference buildings under Typical weather year (TDYMultiple) scenario in compare to demand under TDY, ECY and EWY all together ($Triple_{Multiple}$) scenario. Blue is used for $TDY_{Multiple}$ and red color is for $Triple_{Multiple}$ weather file.

The most remarkable result to emerge from Figure 10 is the impact of taking into consideration extreme values on the distribution of cooling demand, specifically peak values. Almost all the peak cooling demand values of all buildings are considerably higher for the $Triple_{Multiple}$ case than for the $TDY_{Multiple}$ case. This means that designing energy systems based on peak values for typical weather conditions is not the most reliable approach for future climatic conditions of stronger extreme events. The 'triple' approach allows the assessment of building performance not only under typical conditions, but also considering extreme weather conditions. Actual energy demand in commercial buildings is frequently demonstrated to be much greater than the expected energy demand obtained from the energy modeling of the buildings. This difference, often referred to as the energy performance gap, means that actual energy demand can be two to three times the modeled energy demand [100]. Much of the focus in reducing the energy performance gap is on post-construction elements such post-occupancy evaluation and continuous commissioning. Improvements in the energy simulation, such as the consideration of extreme weather conditions, however play a key role for new builds and energy-focused refurbishments.

Table 10 presents the peak loads of the cooling demand with the date and time of occurrence for each of the 16 buildings, typical and extreme warm conditions taken into consideration. The magnitude of the peaks and the time in which they occur are different for each building. This is obviously due to the variance in the type of buildings, their characteristics and their operation schedules. The peak values for $EWY_{Multiple}$ compared to $TDY_{Multiple}$ ranges from a 2 % increase for the hospital to a 28.5 % increase for the sit-down restaurant. The findings from Figure 10 and Table 10 illustrate the importance of considering extreme conditions and the usefulness of the suggested approach in ensuring a robust design of buildings and energy systems for the future.

Table 10. Value of Peak cooling demand and the date-time of occurrence under NT for all buildings and the virtual neighborhood, values for dynamical-typical and dynamical-extreme are presented and compared.

Building name	**Dynamical-typical $TDY_{Multiple}$**		**Dynamical-extreme $EWY_{Multiple}$**		**Peak cooling load relative change $EWY_{Multiple}$ to $TDY_{Multiple}$ (%)**
	Peak load for cooling (kW)	**Date-Time**	**Peak load for cooling (kW)**	**Date-Time**	
High-rise Apartment	59.97	19 Jul-17:00	62.27	24 Jul-19:00	3.8 %
Mid-rise Apartment	18.76	19 Jul-15:00	21.22	27 Jul-15:00	13.1 %
Hospital	235.01	20 Jun-15:00	239.67	24 Jul-15:00	2.0 %
Large Hotel	147.61	28 Jul-19:00	172.21	19 Jul-16:00	16.7 %
Small Hotel	34.71	19 Jul-16:00	38.06	27 Jul-16:00	9.6 %
Large Office	430.21	20 Jun-17:00	453.95	24 Jul-15:00	5.5 %
Medium Office	63.03	19 Jul-15:00	70.55	27 Jul-16:00	11.9 %
Small Office	5.00	19 Jul-16:00	5.47	27 Jul-16:00	9.5 %
Outpatient Healthcare	93.32	20 Jun-15:00	100.82	7 Jul-16:00	8.0 %
Restaurant Fast-food	11.30	19 Jul-13:00	14.16	3 Jul-18:00	25.4 %
Restaurant sit-down	17.96	19 Jul-12:00	23.08	3 Jul-18:00	28.5 %
Standalone Retail	34.69	19 Jul-15:00	42.29	27 Jul-15:00	21.9 %
Strip Mall Retail	30.57	19 Jul-15:00	38.64	27 Jul-15:00	26.4 %
Primary School	97.27	20 Jun-15:00	109.06	13 Jun-15:00	12.1 %
Secondary School	316.51	20 Jun-15:00	348.09	13 Jun-15:00	10.0 %
Warehouse	5.54	19 Jul-16:00	6.78	27 Jul-17:00	22.5 %
Neighborhood	3457.14	19 Jul-16:00	3753.82	27 Jul-16:00	8.6 %

In the second part of our analysis on the impact of extreme conditions, we assess the impacts on high peak energy demand loads on the virtual neighborhood defined in section 3.2.2. The last row of Table 10 presents the peak cooling demand load and the date and time of occurrence for the entire neighborhood. The relative change of peak load in extreme conditions compared to typical conditions is an increase of 8.6 %.

As shown in Table 10, the need for air conditioning increases dramatically during extreme hot conditions. This high demand can last for days to weeks. Additionally, as mentioned before, the production capacity of power plants can be affected during this period. For example, as described by Ke et al. [101], heat waves are usually accompanied by stationary high pressure zones, resulting in light winds at the surface and therefore reduced wind generation. Increased air temperature also causes a reduction in capacity and the efficiency of gas-turbines. Even electricity transmission line loss is affected by high ambient temperature. These chains of events and high demands for a period of time implies high stress on the grid, which can lead to the failure of the system, as in the 2006 heat wave in New York City [102]. Electrical power demand of the virtual neighborhood under typical and extreme conditions was calculated to illustrate such risks at the urban scale. Figure 11 shows the power demand for the neighborhood during the week of the peak loads for $EWY_{Multiple}$ compared to TMY and $TDY_{Multiple}$ under NT. Electric power demand was calculated by adding up for each hour the delivered energy for total electricity (defined in section 3.2.3) for all the buildings in the neighborhood.

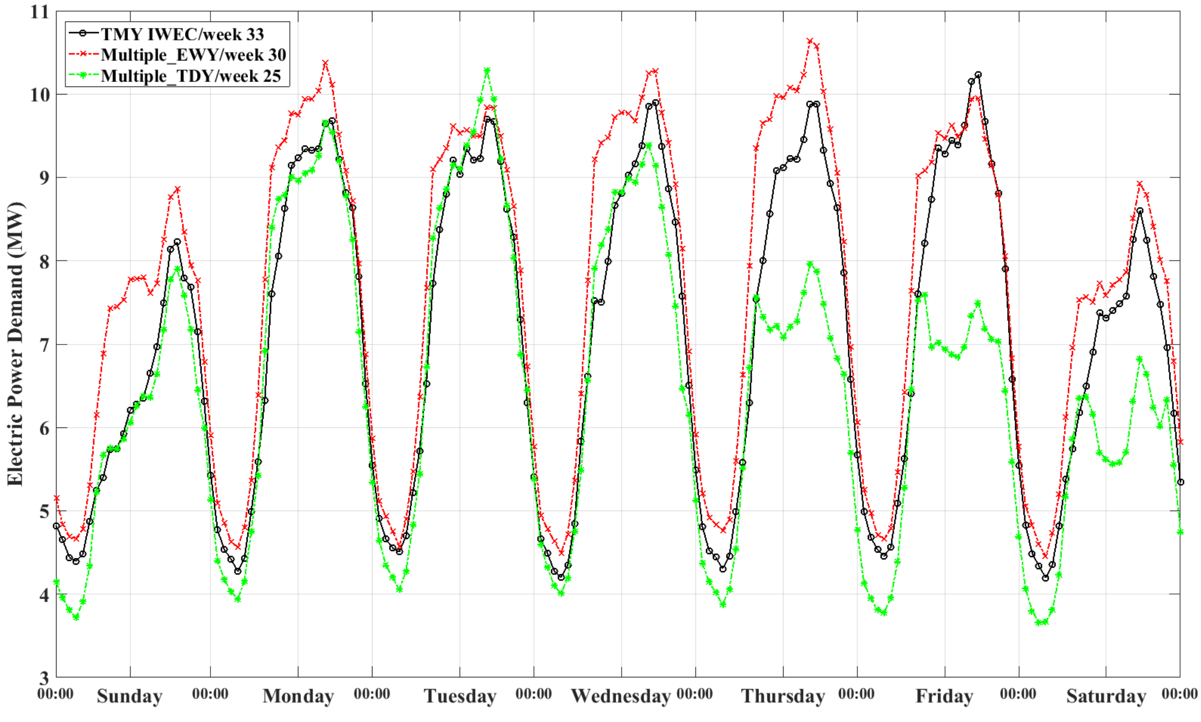

Figure 11. The electrical load profile of virtual neighborhood for a peak summer week in Geneva, considering historical typical weather year (TMY), future typical weather year (TDYMultiple) and future extreme warm weather year (EWYMultiple) under NT.

The minimum level of electricity demand required over a period of 24 hours is referred as 'base load'. For the virtual neighbourhood based on Figure 11, under TMY IWEC this value is around 4.5 MW. This increased throughout the five-day workweek, passing 9 MW and during the weekend remaining below 9 MW at peak. Base load is the minimum power generation requirement and is usually covered by dedicated base-load power plants [103]. The criticality is during the peak load hours, which are from 2 pm to 6 pm on weekdays and 4 pm to 9 pm during the weekend, in the case of the virtual neighborhood. The so-called peak-load power plants are usually used to cater for the demand peaks. They have a relatively high fuel cost compared with base-load power plants and they are started up whenever there is a spike in demand and stopped when the demand recedes. For the neighborhood, the peak value for TMY occurs on Friday 18 August at 5 pm, the value being 10.23 MW. This value for $TDY_{Multiple}$ is slightly higher than TMY and is 10.29 MW on Tuesday 20 June at 4 pm. The peak values for the extreme case $EWY_{Multiple}$ is above 10.28 MW for 4 days, the highest value being 10.64 MW on Thursday 27 July at 4 pm. The hourly electricity demand during the days of extreme conditions furthermore stays above values of typical conditions for almost the whole week. The peak electricity demand values for the neighborhood for $EWY_{Multiple}$ under MT and LT are 11.01 MW and 11.95 MW respectively. This means that the value of peak electricity demand can increase by 4.0 %, 7.6 % and 16.8 % for extreme conditions under NT, MT and LT in relation to the TMY IWEC value. Power plants can, as described before, suffer reductions in efficiency during extreme conditions (heat waves), with a consequential reduction in the capacity of the energy system to cover peaks. Taking into account these issues and looking into the increase in electricity demand for the virtual neighborhood under extreme conditions, it might become a challenge for the energy system of this neighborhood to cover the margin, especially in the likely event of a reduction in generation capacity. The simulation test bench used in this study is developed based on 2013 version of ASHRAE 90.1 standard, which means the models are compliant with a recent energy code. Therefore, the above impacts can be magnified considerably if considering presence of older buildings with envelopes that have lower thermal performance; hence their energy performance is more sensitive to climate conditions. The single most marked observation that emerges from data comparison is the importance of considering extreme conditions to assure the robustness of the designed buildings or energy systems.

5 Conclusions

In this work, the dynamical and statistical methods for downscaling the outputs of GCMs were discussed and two approaches for preparing future weather data for building energy simulations were investigated, one based on using only typical weather conditions and the other based on using typical and extreme conditions. 74 weather files for the city of Geneva, Switzerland were generated using the methods and approaches considered. These were used to understand and compare the assumptions, limitations and advantages of the methods and approaches in predicting the future energy conditions of buildings. According to the results, weather files of the statistical data group are able to present the long-term impacts of climate change on averages (e.g. a gradual increase in the average dry-bulb temperature for Geneva). However, these files are not suitable for investigating the short-term changes that induce extreme weather conditions.

The ASHRAE standard 90.1 suite for commercial buildings was used to study the impacts of the future weather data type on the energy simulation of buildings. This suite of models allows reasonably realistic building characteristics for small office buildings to large energy-intensive buildings such as hospitals, and mid to high-rise residential buildings. According to the results, all the considered types of typical weather data sets provide enough information to study the log-term shift in energy use of the buildings and using the weather files generated by statistical methods can be sufficient. Moreover, typical weather files generated from dynamically downscaled data would also reveal the shifting of energy.

This worked investigated the importance of considering extreme conditions and the possible consequences of neglecting such conditions in designing buildings at building level and neighborhood scale. The approach proposed by Nik [46] was used to generate representative weather files. This approach is based on synthesizing three weather data sets for each 30-year period: typical downscaled year (TDY), extreme cold year (ECY) and extreme warm year (EWY). Firstly, the number of hot days and tropical nights were calculated for different types of weather files according to the definitions of MeteoSwiss. These values were compared to the values observed during the extreme heat wave of the summer of 2003. The results showed only the value derived from the extreme weather file is comparable with the number of hot days that occurred during the summer of 2003 in Geneva. This number is considerably small for the cases where only typical weather data sets (TMY and TDY) are considered. Furthermore, a group of representative weather data sets based on multiple climate scenarios ($TDY_{Multiple}$, $ECY_{Multiple}$ and $EWY_{Multiple}$) were considered to evaluate the impacts of extreme conditions on the energy performance of all 16 buildings and a virtual neighborhood. According to the results, for the near-term future, the range of relative change of peak load for cooling demand under extreme conditions shows an increase of 2 % to 28.5 %, compared to typical conditions depending on the building type. Furthermore, the analysis of the virtual neighborhood revealed that the peak electric power demand for the neighborhood can increase by 4.0 %, 7.6 % and 16.8 % under near-term, medium-term and long-term future for extreme conditions in relation to the value calculated using the TMY file. These results underline the importance of considering extreme conditions in studying the impacts of climate change on larger spatial scales (e.g. urban and city scales) and preparing urban energy systems for future conditions.

The focus of this paper was on the impacts of long-term patterns of climate change and extreme weather conditions on the energy performance of buildings. Future work should be undertaken using different methods of generating future weather files to study the thermal stress upon building occupants. It might, furthermore, be necessary to consider the effects of urban/micro climate (depending on the case), as the effects of climate change might be amplified or diminished at the urban scale, especially for extreme conditions.

In conclusion, our work provided further evidence that proper weather data sets based on high resolution data from climate models and several climate scenarios, including extreme conditions, are required to empower building engineers and architects to test their design solutions under future climate uncertainties. As discussed before, a large part of literature with focus on the impacts of future climate conditions on the performance of buildings are from the UK, where such weather files are readily accessible for several locations. It shows that the availability of such files is crucial and requires efforts at national levels. Only this type of approach will involve more experts into the discussion of finding solutions that guarantee a more robust and climate resilient built environment in the future.

6 Acknowledgements

This work has been written within the Research Centre on Zero Emission Neighborhoods in Smart Cities (FME ZEN). The authors gratefully acknowledge the support of the ZEN partners and the Research Council of Norway. This work has partly benefited from the support of the Swedish Research Council (Formas) which is gratefully acknowledged.

7 Annex A

No.	Title	Year	Country
1	Climate change impacts on the thermal performance of Portuguese buildings. Results of the SIAM study	2002	Portugal
2	Climate change impacts on building heating and cooling energy demand in Switzerland	2005	Switzerland
3	The impact of climate change uncertainties on the performance of energy efficiency measures applied to dwellings	2005	UK
4	Climate change, thermal comfort and energy: Meeting the design challenges of the 21st century	2007	UK
5	Creating weather files for climate change and urbanization impacts analysis	2007	US
6	Embodied and operational carbon dioxide emissions from housing: a case study on the effects of thermal mass and climate change	2008	UK
7	Estimating the impacts of climate change and urbanization on building performance	2008	US
8	Beyond TMY: climate data for specific applications.	2008	Australia
9	Uncertainties in predicting the impact of climate change on thermal performance of domestic buildings in the UK	2008	UK
10	Climate change future proofing of buildings-Generation and assessment of building simulation weather files	2008	UK
11	Evaluating the potential impact of global warming on the UAE residential buildings - A contribution to reduce the CO2 emissions	2009	United Arab Emirates
12	Will future low-carbon schools in the UK have an overheating problem?	2009	UK
13	Resilience of naturally ventilated buildings to climate change: advanced natural ventilation and hospital wards	2009	UK
14	Identification of key factors for uncertainty in the prediction of the thermal performance of an office building under climate change	2009	UK
15	Assessment of climate change impact on residential building heating and cooling energy requirement in Australia	2010	Australia
16	The effects of future climate change on heating and cooling demands in office buildings in the UK	2010	UK
17	Predicting the performance of an office under climate change: a study of metrics, sensitivity and zonal resolution	2010	UK
18	Comparison of multi-year and reference year building simulations	2010	UK
19	Predicted changes in energy demands for heating and cooling of passive house due to climate change in Slovenia	2010	Slovenia
20	The role of adaptive thermal comfort in the prediction of the thermal performance of a modern mixed-mode office building in the UK under climate change	2010	UK
21	Translating probabilistic climate predictions for use in building simulation	2010	UK
22	Climate change adaptation pathways for Australian residential buildings	2011	Australia
23	Developing future hourly weather files for studying the impact of climate change on building energy performance in Hong Kong.	2011	Hong Kong
24	A probabilistic analysis of the future potential of evaporative cooling systems in a temperate climate	2011	UK
25	The impact of the projected changes in temperature on heating and cooling requirements in Dhaka, Bangladesh	2011	Bangladesh
26	Longitudinal prediction of the operational energy use of buildings	2011	UK
27	Climate change, building design, and thermal performance	2011	Austria
28	Assessing the risk of climate change for buildings: A comparison between multi-year and probabilistic reference year simulations	2011	UK
29	Designing net-zero energy buildings for the future climate, not for the past	2012	Canada
30	Future energy demand for buildings in the context of climate change for Burkina Faso	2012	Burkina Faso
31	Generating design reference years from the UKCP09 projections and their application to future air-conditioning loads	2012	UK
32	The natural ventilation performance of buildings under alternative future weather projections	2012	UK

33	Thermal mass in new build UK housing: a comparison of structural systems in a future weather scenario	2012	UK
34	Ranking of interventions to reduce dwelling overheating during heat waves.	2012	UK
35	Climate change influence on building lifecycle greenhouse gas emissions: case study of UK mixed-use development	2012	UK
36	Energy use, indoor temperature and possible adaptation strategies for air-conditioned office buildings in face of global warming	2012	Australia
37	Using UK climate change projections to adapt existing English homes for a warming climate	2012	UK
38	A proposed method to assess the damage risk of future climate change to museum objects in historic buildings	2012	Netherlands and Belgium
39	Thermal comfort standards, measured internal temperatures and thermal resilience to climate change of free-running buildings: a case-study of hospital wards	2012	UK
40	Assessment of hygrothermal performance and mould growth risk in ventilated attics in respect to possible climate changes in Sweden	2012	Sweden
41	Building characteristics as determinants of propensity to high indoor summer temperatures in London dwellings	2012	UK
42	A comparison of structural and behavioural adaptations to future proofing buildings against higher temperatures	2012	UK
43	Management of thermal performance risks in buildings subject to climate change	2012	UK
44	Simulating urban heat island effects with climate change on a Manchester house	2012	UK
45	Impact of climate change on thermal comfort and energy performance in offices - A parametric study	2012	Greece
46	Impact of climate change on comfort and energy performance in offices	2012	Greece
47	A comparative analysis of current and newly proposed overheating criteria for UK schools: A climate change aspect	2012	UK
48	Simulation of the impact of climate change on the current building's residential envelope thermal transfer value (ETTV) regulation in Singapore	2012	Singapore
49	Summertime impact of climate change on multi-occupancy British dwellings	2012	UK
50	Climate data and climate change - Analysis of the influence on energy demand, performance requirement and thermal comfort of buildings [Klimadaten und Klimawandel - Untersuchungen zum Einfluss auf den Energiebedarf, den Leistungsbedarf und den thermischen Komfort von Gebäuden]	2012	Germany
51	Comparison of untypical meteorological years (UMY) and their influence on building energy performance simulations	2013	Poland
52	Energy simulation of sustainable air-cooled chiller system for commercial buildings under climate change	2013	Honk Kong
53	The effectiveness of retrofitting existing public buildings in face of future climate change in the hot summer cold winter region of China	2013	China
54	Modelling to predict future energy performance of solar thermal cooling systems for building applications in the North East of England	2013	UK
55	An investigation into future performance and overheating risks in Passivhaus dwellings	2013	UK
56	Transforming existing weather data for worldwide locations to enable energy and building performance simulation under future climates	2013	UK
57	Building envelope design for climate change mitigation: a case study of hotels in Greece	2014	Greece
58	Impacts of urban location and climate change upon energy demand of office buildings in Vienna, Austria	2014	Austria
59	Impact of climate change heating and cooling energy use in buildings in the United States	2014	US
60	An outdoor-indoor coupled simulation framework for Climate Change-conscious Urban Neighborhood Design	2014	Egypt
61	Risks of summertime extreme thermal conditions in buildings as a result of climate change and exacerbation of urban heat islands	2014	US
62	Effects of future climate change scenarios on overheating risk and primary energy use for Swedish residential buildings	2014	Sweden
63	Climate change simulation for intelligent green building adaptation design	2014	UK

64	Microclimate change outdoor and indoor coupled simulation for passive building adaptation design	2014	UK
65	Sampling-based sensitivity analysis of thermal performance in domestic buildings under climate change	2014	UK
66	Environmental benefits of sustainable chiller system under climate change	2014	Hong Kong
67	Double-skin façades in the context of climate change [Doppelfassaden im Zeichen des Klimawandels]	2014	Germany
68	Impacts of climate change upon cooling and heating energy demand of office buildings in Vienna, Austria	2014	Austria
69	Analysis of performance of night ventilation for residential buildings in hot-humid climates [Sicak-nemli iklimlerdeki konut binalarinda gece havalandirmasi performansinin analizi]	2014	Turkey
70	Impact of building design and occupancy on office comfort and energy performance in different climates	2014	Creece, Germany, Australia
71	Developing a probabilistic tool for assessing the risk of overheating in buildings for future climates	2014	UK
72	Near Future Weather Data for Building Energy Simulation in Summer/Winter Seasons in Tokyo Developed by Dynamical Downscaling Method	2014	Japan
73	Generating near-extreme Summer Reference Years for building performance simulation.	2015	UK
74	Climate for Culture: assessing the impact of climate change on the future indoor climate in historic buildings using simulations	2015	Whole Europe
75	Energy demand for the heating and cooling of residential houses in Finland in a changing climate	2015	Finland
76	Impacts of climate change on energy consumption and peak demand in buildings: A detailed regional approach	2015	US
77	Preparing for climate change with computation and resiliency	2015	US
78	Study on the future weather data considering the global and local climate change for building energy simulation	2015	Japan
79	The potential of phase change materials to reduce domestic cooling energy loads for current and future UK climates	2015	UK
80	Future moisture loads for building facades in Sweden: Climate change and wind-driven rain	2015	Sweden
81	Vulnerability to climate change impacts of present renewable energy systems designed for achieving net-zero energy buildings	2016	US
82	Effect of climate change on building cooling loads in Tokyo in the summers of the 2030s using dynamically downscaled GCM data	2016	Japan
83	Future trends of residential building cooling energy and passive adaptation measures to counteract climate change: The case of Taiwan.	2016	Taiwan
84	Integrating climate change and energy mix scenarios in LCA of buildings and districts	2016	France
85	Modeling the long-term effect of climate change on building heat demand: Case study on a district level	2016	Portugal
86	Climate change future proofing of buildings—Generation and assessment of building simulation weather files.	2016	Italy
87	Future probabilistic hot summer years for overheating risk assessments.	2016	UK
88	Optimization of annual energy demand in office buildings under the influence of climate change in Chile	2016	Chile
89	Impact of climate change on heating and cooling energy demand in houses in Brazil	2016	Brazil
90	Residential buildings' thermal performance and comfort for the elderly under climate changes context in the city of Sao Paulo, Brazil	2016	Brazil
91	Analysis of the predicted effect of passive climate adaptation measures on energy demand for cooling and heating in a residential building	2016	Netherlands
92	The impact of regulations on overheating risk in dwellings	2016	UK
93	Impact of future climates on the durability of typical residential wall assemblies retrofitted to the PassiveHaus for the Eastern Canada region	2016	Canada
94	Impacts of climate change on U.S. building energy use by using downscaled hourly future weather data	2017	US
95	Prediction of the impacts of climate change on energy consumption for a medium-size office building with two climate models. Energy and Buildings	2017	US
96	Climate Change Adaptation Pathways for Residential Buildings in Southern China.	2017	China

97	Influence of climate change on summer cooling costs and heat stress in urban office buildings	2017	Belgium
98	Making energy simulation easier for future climate – Synthesizing typical and extreme weather data sets out of regional climate models (RCMs)	2017	Sweden
99	Application of adaptive comfort behaviors in Chilean social housing standards under the influence of climate change	2017	Chile
100	Cooling Energy Implications of Occupant Factor in Buildings under Climate Change	2017	South korea and Hong kong
101	Assessment of climate change impact on the required cooling load of the hospital buildings	2017	Malaysia
102	Adapting the design of a new care home development for a changing climate	2017	UK
103	The impact of climate change on the overheating risk in dwellings—A Dutch case study	2017	Netherlands
104	Energy Consumption Performance Considering Climate Change in Office Building	2017	China
105	Performance evaluation of well-insulated versions of contemporary wall systems-a case study of London for a warmer climate	2017	UK
106	Robustness of residential houses in Ecuador in the face of global warming: Prototyping and simulation studies in the Amazon, coastal and Andes macroclimatic regions	2017	Ecuador
107	Effectiveness of passive measures against climate change: Case studies in Central Italy	2017	Italy
108	Energy efficiency and resilience against increasing temperatures in summer: The use of PCM and cool materials in buildings	2017	Italy
109	Should we consider climate change for Brazilian social housing? Assessment of energy efficiency adaptation measures	2018	Brazil
110	A dynamic modelling approach for simulating climate change impact on energy and hygrothermal performances of wood buildings	2018	Finland
111	Cooling and heating energy performance of a building with a variety of roof designs; the effects of future weather data in a cold climate	2018	Canada

8 Annex B

Boxplots of the global horizontal radiation, relative humidity and wind speed as some of the key variables for energy simulation, are plotted in Figure A.1, Figure A.2 and Figure A.3 respectively.

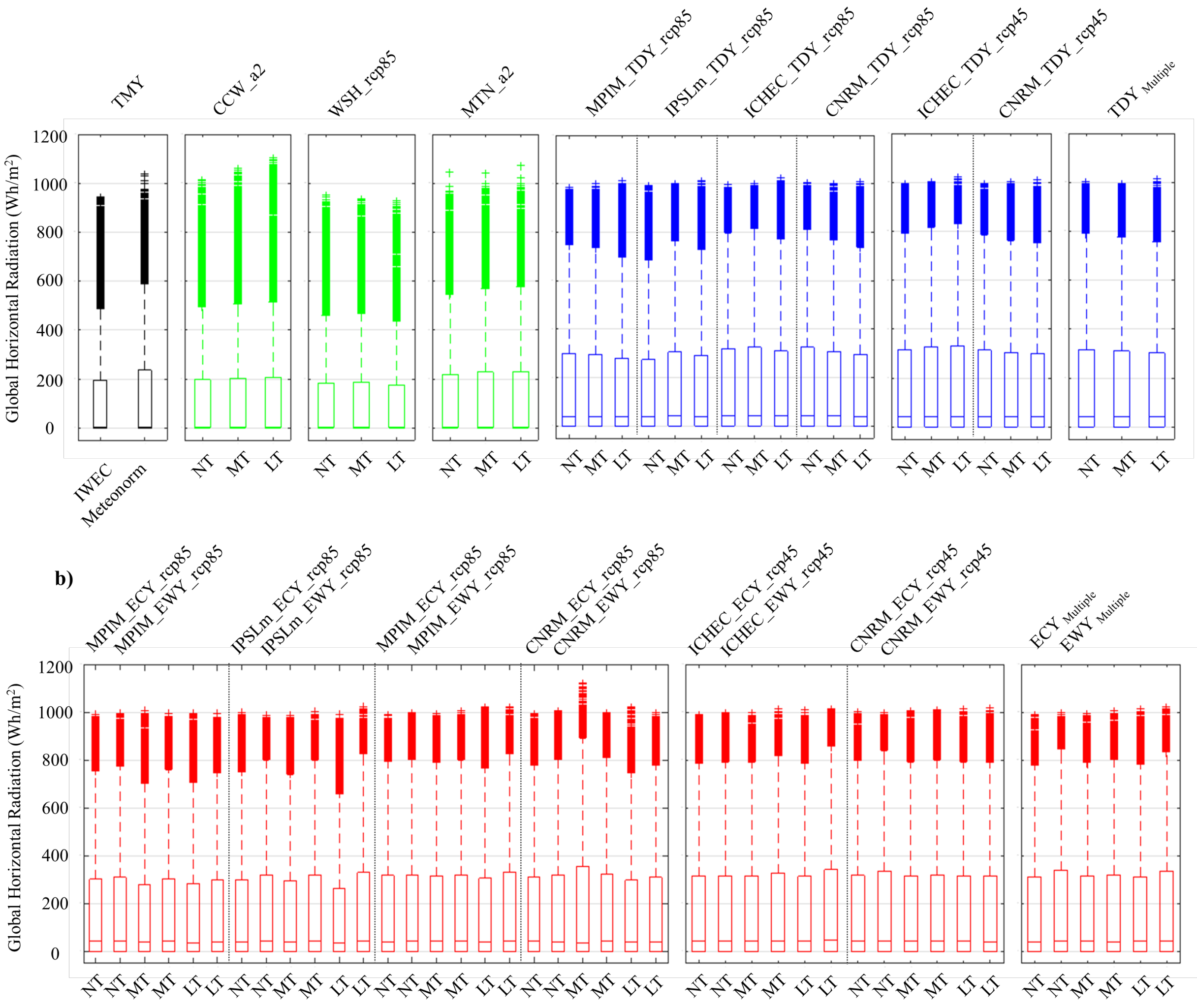

Figure B.1. Boxplots of global horizontal radiation for the weather files generated by three software tools–CCWorldWeatherGen, WeatherShiftTM, Meteonorm –and six combinations of GCM-RCMs with different emission scenarios.

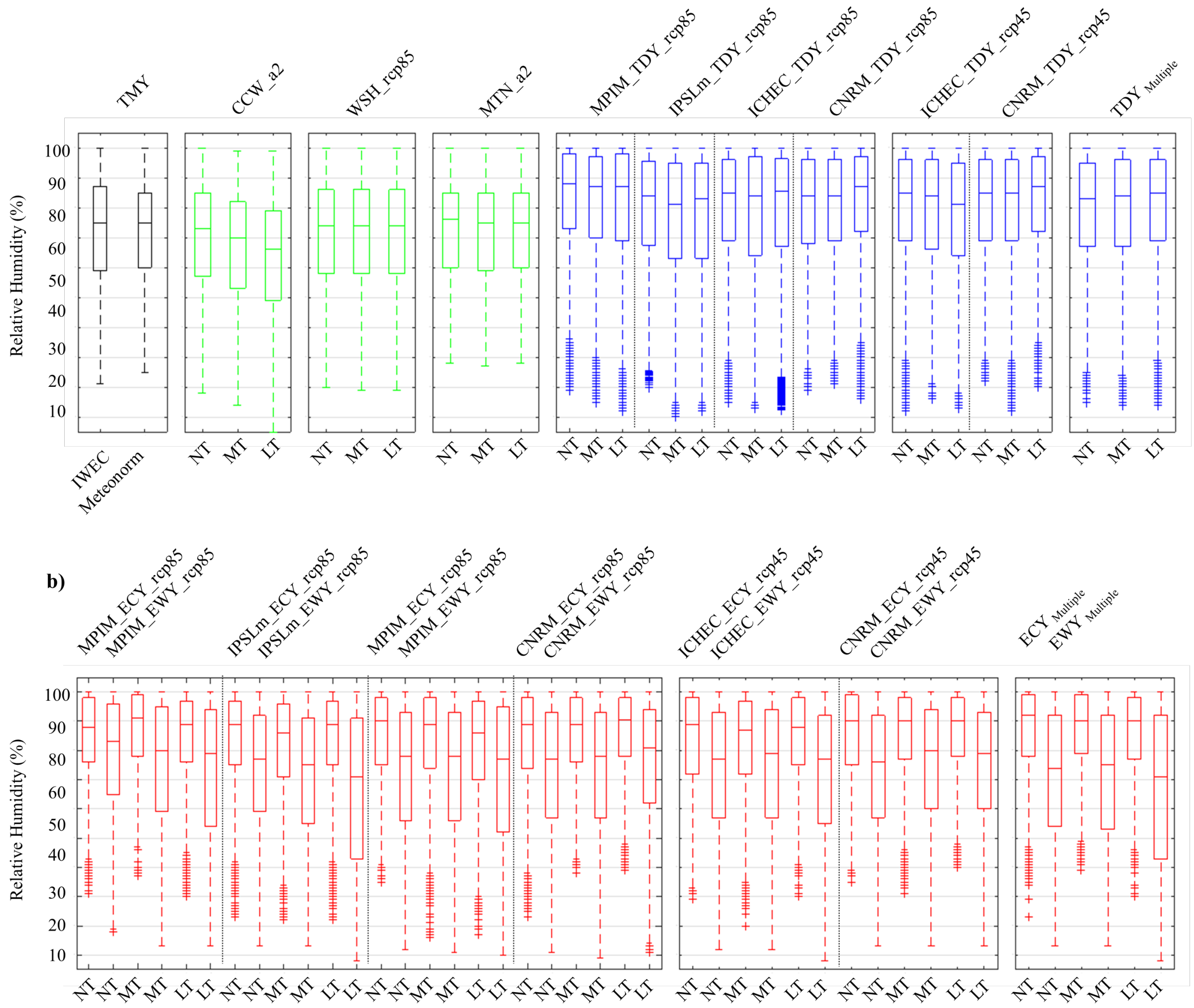

Figure B.2. Boxplots of relative humidity for the weather files generated by three software tools– CCWorldWeatherGen, WeatherShiftTM, Meteonorm –and six combinations of GCM-RCMs with different emission scenarios.

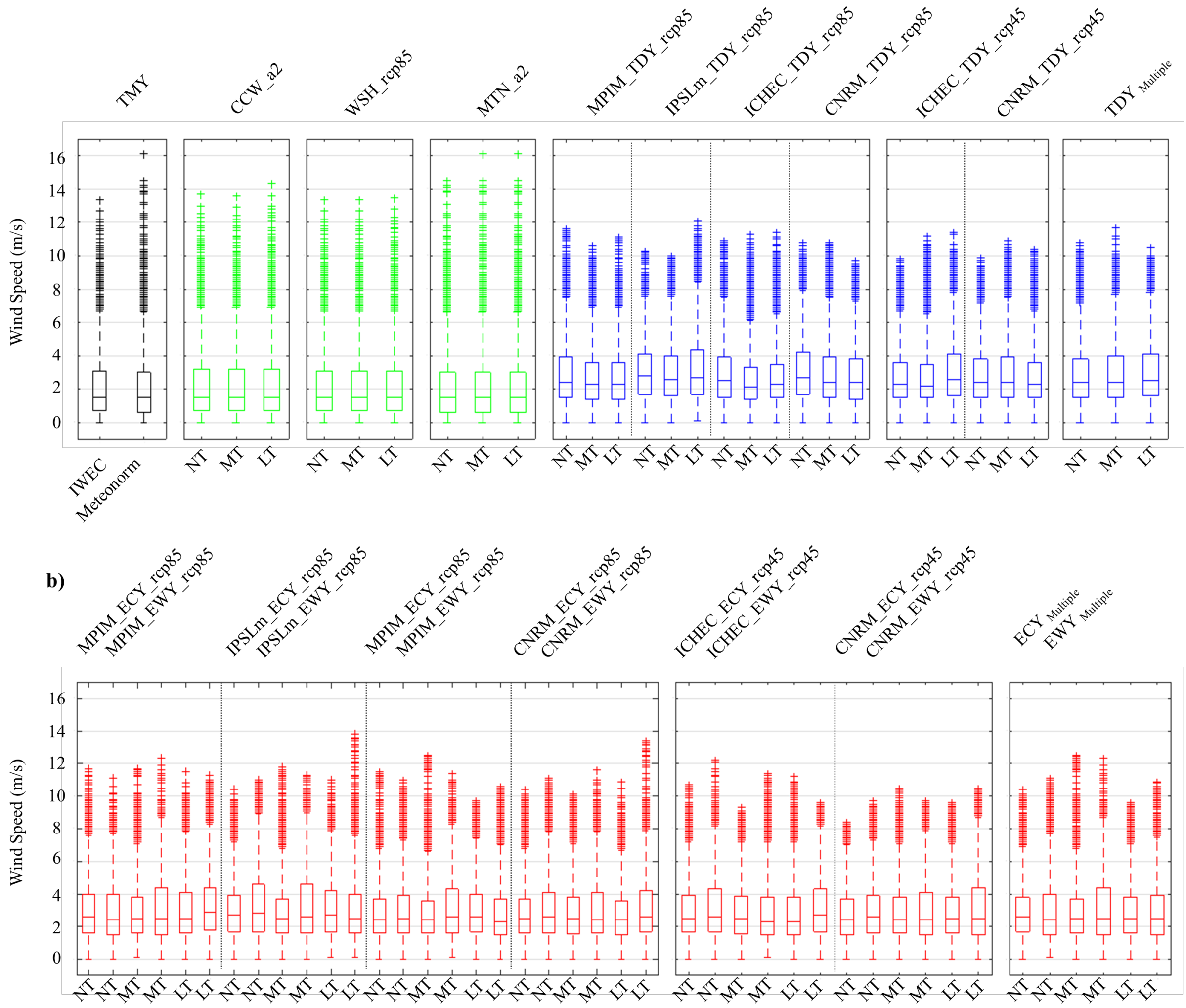

Figure B.3. Boxplots of wind speed for the weather files generated by three software tools– CCWorldWeatherGen, WeatherShiftTM, Meteonorm –and six combinations of GCM-RCMs with different emission scenarios.

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