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Investigating the importance of future climate typology on estimating the energy performance of buildings in the EPFL campus

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Abstract

Climate changes induce warmer climate with stronger and more frequent extreme events. Due to the uncertain nature of climate, accurate simulation of future conditions is impossible and a major challenge is the selection of climate data in the impact assessment. This work compares application of three climate data sets in an energy simulation of the EPFL campus: i) Regional Climate Models (RCM data), ii) statically representative RCM data, and iii) morphed data. The energy behavior of the campus is analyzed, including its future thermal behavior, as well as its dynamic hourly variation due to the climatic data. The objective of this paper is to understand and quantify the energy transition, from 2010 to 2100, by focusing on the thermal behavior of buildings, as well as their energy demand for heating and cooling. Results explain the difference between three cases, underling the important impact related to a sound selection of the weather data.

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Keywords: climate change; energy simulation; climate uncertainty; weather data; extreme conditions

1. Introduction

Climate change can affect the performance of buildings and energy systems, dictating new conditions which most probably will not be in line with those we are used to. One of the major features of future climate is the more

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frequent and stronger occurrence of extreme events. Studying impacts of climate change on buildings, as the key components of cities, has been subject of interest for the last few years and several research works are available, mostly focused on energy issues e.g. [1, 2]. The source and type of the future weather data are important and can induce considerable variations in the impact assessment [2, 3]. The simplest approach is defining future weather data only by changing the average of the available weather data. Although this works for simple tasks, future climate variations and extremes will be neglected. A more scientifically valid approach is to use what climate scientists have produced by simulating the future climate conditions and extract data from global climate models (GCMs). The outcome of GCMs cannot be directly applied in energy simulations and should be downscaled using statistical or dynamical methods. One widely used statistical downscaling technique is the morphing technique [4] which combines present-day observed weather data with the GCM results. The morphing technique reflects only changes in the average weather conditions and not the variations in weather sequences [5]. Dynamic downscaling of GCMs by means of regional climate models (RCMs) generates physically consistent data sets [6] with suitable temporal and spatial resolutions for energy simulations. A valid impact assessment needs considering long time periods and several climate scenarios which results in large data sets and uncertainties (e.g. [7, 8]).

This work investigates the energy performance of the campus of Ecole Polytechnique Fédérale de Lausanne (EPFL) in Switzerland for the future, considering several climate scenarios and three different types of weather data sets, generated by RCMs, synthesizing the RCM data and morphing GCM data. The energy performance of the campus is simulated for the period of 2010-2100, considering three 30-year periods in CitySim. The aim of this research is assessing the probable future energy conditions of the campus, investigating the differences induced by weather data, and the energy transition between 2010 and 2100.

2. Methodology

2.1. Future climate scenarios

Three types of climate data are used in this work which are briefly described in the following. The first two data sets are for Geneva, while the third data set is for Lausanne. Although weather conditions in Lausanne and Geneva are very similar, it should be noted that using data for different cities can introduce some divergence in the results.

2.1.1. RCM weather data

Several climate scenarios for the city of Geneva (until 2100) were synthesized out of the RCA4 model. The weather data have the temporal and spatial resolutions of one hour and 12.5 km respectively. Five future climate scenarios, having four different GCMs and two different RCPs, are considered in this work. GCMs are: 1) CNRM-CM5, 2) ICHEC-EC-EARTH, 3) IPSL-CM5A-MR, 4) MPI-ESM-LR (for details, see [9]). GCMs are forced by two Representative Concentration Pathways (RCPs), RCP4.5 and RCP8.5.

2.1.2. Synthesized RCM data (typical and extremes)

The second type of weather data are synthesized based on the distribution of all the RCM data sets. The synthesized data contain 3 sets of one-year weather data, representing typical, extreme cold and extreme warm conditions. these data sets are called typical downscaled year (TDY), extreme cold year (ECY) and extreme warm year (EWY). For each 30-year period, there will be one TDY, ECY and EWY, representing the whole period and all the considered climate scenarios (for details, see [9]).

2.1.3. Morphed data

The third type of weather data are generated by Meteonorm. The future climate data sets generated by Meteonorm are based on the 4th IPCC Special Report on Emission Scenarios (SRES - AR4), considering three emission scenarios of A2, A1B and B1 with the approximate carbon dioxide equivalent concentrations of 1250, 850 and 600 ppm in 2100, respectively. Future weather data generated by Meteonorm are based on using a simple autoregressive model which is used to generate realistic monthly time series, quite similar to what happens in the morphing technique [4].

2.2. The energy model of the EPFL campus

The EPFL campus is located near the city of Lausanne (46° 31' N, 06°38' E, 495 m a.s.l.) and Lake Geneva. The campus is composed of more than 50 buildings, interconnected by a pedestrian circuit. The university campus was constructed in three main stages: first stage from 1972 to 1984, second stage from 1980 to 1992 and third stage from 1992 to 2002 [10, 11]. The envelopes of each period of construction are calculated by Lesosai [12]. The physical properties of the envelope according to the period of construction are summarized in Table 1: all new buildings present a common envelope; they have been built after 2001 and consequently comply with the energy requirements defined by the Swiss Norm SIA 380/1.

Table 1. Envelope of the buildings, defined according to their period of construction.

Construction stage	U-value Roof ($W \cdot m^{-2}K^{-1}$)	U-value Wall ($W \cdot m^{-2}K^{-1}$)	U-value Floor ($W \cdot m^{-2}K^{-1}$)
First Stage (1972-1984)	0.33	0.33	0.56
Second Stage (1980-1992)	0.31	0.38	0.56
Third Stage (1992-2002)	0.31	0.38	0.56
New buildings (since 2002)	0.16	0.16	0.16

The heating set point temperature during the wintertime (21.5°C) and occupancy profile are defined according to the Swiss Norm SIA 2024 [13]. The geometry of the campus is based on an existing 3D model [14]. The proposed energy model of the campus was validated with on-site monitoring, performed by the enterprise ENERGO during the years 2011, 2012 and 2013 [15]. The coefficient of determination between the computational model and the monitoring is equal to 0.89, and the average relative difference corresponds to 10%. This difference is related to the uncertainties of the model (internal gains, occupant behavior as well as deterioration of the physical properties of the envelope) as well as the weather data used for the simulations. In order to perform the energy simulations for the future climatic scenarios, we modified the CitySim code, being able to run the simulations continuously for the next one hundred years. By this new method, we could quantify dynamically the future thermal behavior of the campus, continuously throughout time.

3. Results

Weather data sets and their consequent energy simulation results are assessed in the following, focusing on the outdoor temperature, heating and cooling demand of the campus. In assessing the energy simulation, results of CNRM-rcp45 are not considered.

3.1. Outdoor temperature

The average values of the outdoor temperature and its variations (standard deviation) for the last 30-year period of the 21st century are shown in Fig. 1. The third grey bar represents the absolute average of the one-hour variations during the whole period (to be called relative variations), i.e. the relative difference (in percentage) of the outdoor tempter at time *t+1* compared to time *t*. There are considerable differences between different climate scenarios and data sets. For example, the maximum difference in the periodical average between RCM scenarios is 3.6^{o}C, between IPSL and CNRM. Interestingly, the relative variations have negative correlation with the average temperature; the smaller the average temperature, the larger the relative variation. Representative weather data sets (TDY, ECY and EWY9 and their combination (Triple) represent all the RCM scenarios for their average, standard deviation and relative variations. Differences between Meteonorm data sets are small, since they represent only three difference emission scenarios and not different GCMs, while GCMs induce larger differences. The relative variations are much smaller among Metenorm data sets, which tells about smaller variations in the future weather data sets which are generated by the morphing technique.

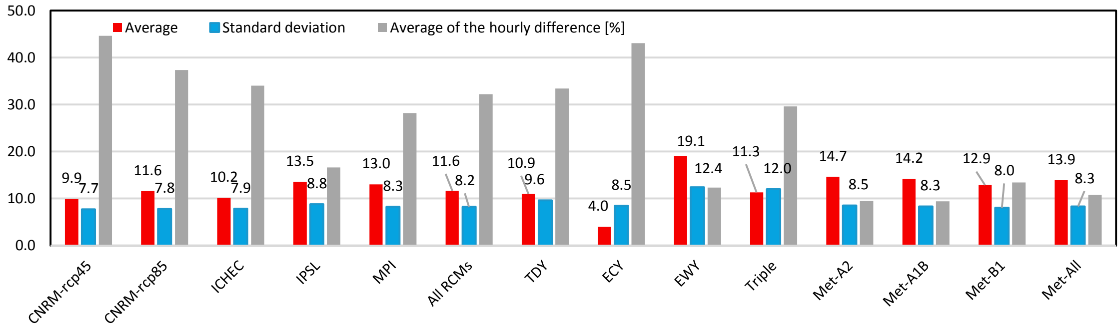

Fig. 1. Average and standard deviation of the hourly outdoor temperature [ºC] together with the absolute average of the relative variations of the hourly temperature [%] for five different RCMs and all of them together, representative data sets (TDY, ECY and EWY) and their combination (Triple) as well as morphed weather data by Meteonorm (Met-A2, -A1B and –B1) and their combination (Met-All). All weather data sets are for the last 30 years of the 21st century.

3.2. Energy performance

The average and standard deviation of the hourly heating and cooling demand of the whole campus are plotted in Fig. 2, while the annual averages are shown in Table 2, for three 30-year periods and four different climate scenarios. Apparently in all the scenarios the need for heating decreases and for cooling increases. Having relatively large values for the standard deviations, especially for the cooling demand, points to the importance of hourly variations, which can induce more frequent and stronger extreme conditions, resulting in more peak hours with heavy loads on the energy system.

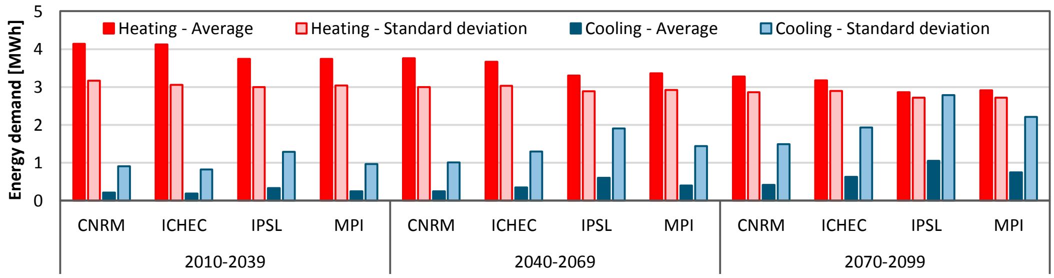

Fig. 2. Average and standard deviation of the hourly energy demand of the EPFL campus [MWh] during three time periods for four climate scenarios.

Table 2. Annual energy demand for the EPFL campus [MWh] during three time periods for four climate scenarios.

	2010-2039				2040-2069				2070-2099			
	CNRM	ICHEC	IPSL	MPI	CNRM	ICHEC	IPSL	MPI	CNRM	ICHEC	IPSL	MPI
Heating	36269	36057	32759	32758	32911	32140	28871	29403	28732	27819	25035	25458
Cooling	1873	1635	2923	2148	2190	3049	5300	3526	3714	5528	9238	6573

Energy simulation results are compared among all the weather data sets. In Fig. 3, boxplots of the hourly heating demand during 2070-2099 are shown. Obviously using only typical weather sets, i.e. TDY and Meteonorm data sets, results in underestimating the extreme conditions. The lower median for the cases with Meteonorm data deals with the fact that the RCM scenarios predict warmer conditions than the GCMs which are considered in Meteonorm. This means that even considering several emission scenarios, the uncertainties induced by climate data are large.

The hourly average of the heating and cooling demand as well as their standard deviations are compared among all the weather data sets in Fig. 4. Naturally the ECY and EWY data sets result in extreme cases, while TDY and Triple produce results representing all the RCM scenarios; the hourly variations are slightly more overestimated for Triple case. The average hourly values are in better agreement with RCM scenario in Fig. 4. The hourly average cooling demand and its variations are larger for cases with Meteonorm weather data. However, the relative variations in Fig. 5 point to the fact that time to time differences are much larger for the RCM scenarios (consider that the values in Fig. 5 are relative differences, but not in percentage), especially for the cooling demand. This means that using the dynamically downscaled weather data out of GCMs potentially introduces larger variations in the hourly time scale, which can be important in designing energy system for urban areas. These relative variations are underestimated even for the representative weather data sets out of RCM scenarios (TDY, ECY, EWY and Triple). This make sense since by representing 30 years in one year, the average hourly variations will be dampened a bit.

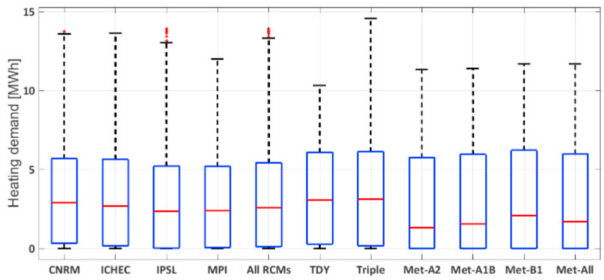

Fig. 3. Distribution of the hourly heating demand of the whole campus during 2070-2099 for four RCMs and their combination, TDY and its combination with extreme weather conditions (Triple), morphed data with three different emissions scenarios (Met-A2, A1B and B1) and their combination (Met-All).

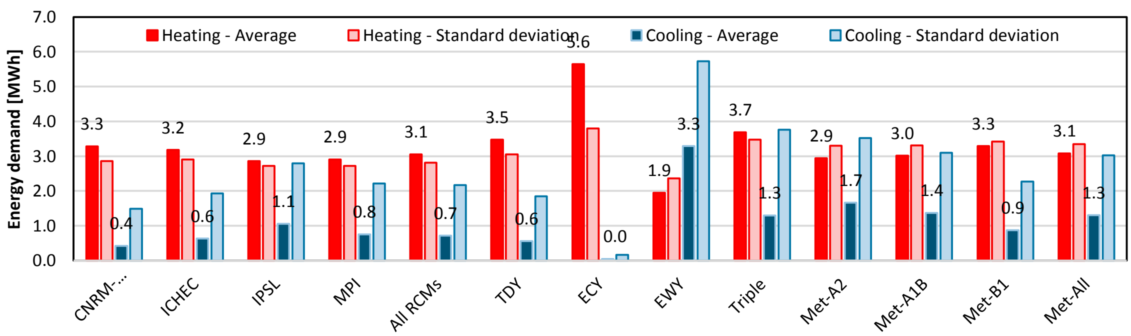

Fig. 4. Average and standard deviation of the hourly heating and cooling demand for energy simulations using four different RCM scenarios and their combination (All RCMs), representative data sets (TDY, ECY and EWY) and their combination (Triple) as well as the Meteonorm data (Met-A2, -A1B and –B1) and their combination (Met-All). All weather data sets are for the last 30 years of the 21[st] century.

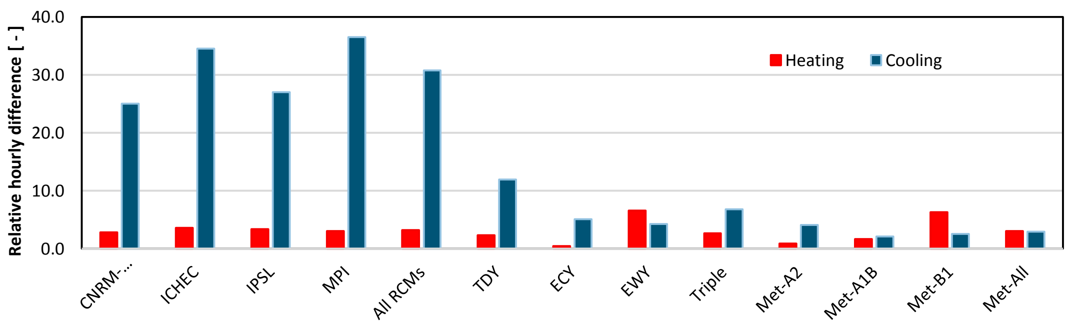

Fig. 5. Absolute average of the relative variations of the hourly energy demand for energy simulations using four different RCM scenarios and their combination (All RCMs), representative data sets (TDY, ECY and EWY) and their combination (Triple) as well as the Meteonorm data (Met-A2, -A1B and –B1) and their combination (Met-All). All weather data sets are for the last 30 years of the 21st century. absolute average of the relative variations of the hourly temperature

4. Conclusions

According to the results, there are considerable differences due to the source of weather data, both on average conditions and their variations. Differences between the dynamically and statistically downscaled data sets are very large for the relative variations in hourly time scale, especially for the cooling demand. This means that using the dynamically downscaled weather data out of GCMs potentially intorduces larger variations in the hourly time scale, which can be important in designing energy systems for urban areas. The relative variations have negative correlation with the average temperature; the lower the average temperature, the larger the relative variation. Having relatively large values for the standard deviations, especially for the cooling demand, points to the importance of hourly variations, which can induce more frequent and stronger extreme conditions, resulting in more peak hours with heavy loads on the energy system.

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