A New Approach to Model the Effect of Climate Change on the Building Sector: a Climate Models Data Fusion

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Abstract

Several climate models have been developed and used to forecast the effects of the climate changes, however the variability of results due to different models lead to a significant uncertainty on the estimation of the building energy use for the next century. In this context, the paper analyses this uncertainty and combines different climate models in order to improve the robustness of energy consumption predictions. The data of the climate models were then used to generate hourly weather files for the future period 2020-2099 and energy simulations for a case study located in Palermo (Italy) were performed. Results show a wide variability among all models (either alone or combined with our data-fusion method), with a mean variability of about 18% of the cooling energy requirements considering the RCP4.5 scenario. This reinforces the need for a more detailed validation and alternative climate change models for building simulation.

Introduction

Climate change is widely acknowledged as a primary environmental problem. In this context, while the technologies to reach a low-carbon building sector already exist (Beccali et al., 2012; Beccali, Cellura, Longo, & Guarino, 2016; Bobba et al., 2018; S Ferrari & Zagarella, 2015; Tumminia et al., 2018), the potential impact of climate change to the building sector is so large that trying to identify future trends and pathways towards decarbonisation is fundamental for a sustainable future (Maurizio Cellura, Guarino, Longo, & Mistretta, 2017; Finocchiaro, Beccali, Cellura, Guarino, & Longo, 2016).

In particular, since the long lifetime of buildings corresponds to the timescale over which the climate is expected to show substantial change, the buildings constructed today need to be resilient to future climates (Beccali, Cellura, & Mistretta, 2007; Guan, 2012; Hamdy, Carlucci, Hoes, & Hensen, 2017). Moreover, climate change could cause worsening of current issues of high performance buildings such as overheating even in non-traditionally cooling dominated countries, coupled with a large increase in power generation needs for cooling (M Cellura et al., 2011; Simone Ferrari & Zanutto, 2012; Robert & Kummert, 2012; Zhai & Helman, 2019).

Predicting future climatic conditions is the starting point to all building climate change impact studies. In this context, different General Circulation Models (GCMs) were developed to obtain predictions of the future climate. GCMs are essentially mathematical models of the general circulation of a planetary atmosphere, which describe the most important components, processes and interactions in the climate system. The GCMs predict climate at a relatively high level of spatial and temporal resolution (typical spatial resolution of 150–600 km (Taylor, Stouffer, & Meehl, 2012)). During the past two decades, GCMs were downscaled to regional climate models (RCMs) by making use of a nesting strategy to obtain climate information at a resolution of 10–100 km (Stocker D. et al., 2013). However, driven by the fact that assessing the impact of climate change on building performance requires local weather data at higher temporal resolution, the GCM or RCM outputs have to be “downscaled”, referring to a process of generating climate change information at spatial and temporal scales lower than those provided by these models.

To adapt GCMs or RCMs outputs and assess the impact of climate change on building performance two different approaches can be usually found in the state of the art: statistical methods and building simulation approaches. Statistical methods were used to model the interactions between the local meteorological variables and the building energy demand based on historical available data. An example is the prediction of building energy consumption using the degree-days approach (Artmann, Gyalistras, Manz, & Heiselberg, 2008; H. Wang & Chen, 2014). It is essentially a steady-state approach aimed at the quantification of building energy use for heating and cooling. This approach is not particularly effective in the context of energy use prediction via detailed dynamic building simulation, as having availability of hourly future weather data is a prerequisite and a key point for the energy demand prediction by taking advantage of building simulation tools (Gupta & Gregg, 2012). In this context, the creation of future weather files is usually approached by a mathematical transformation (morphing) (Belcher, Hacker, & Powell, 2005) of the time series of existing current weather files using climate change forecasts produced by GCMs or RCMs.

Through the Fifth Assessment Report, the Intergovernmental Panel on Climate Change (IPCC) has recommended 58 different GCMs, developed by 23 different research centres, based on the latest 4 IPCC emissions scenarios, called Representative Concentration Pathways (RCP2.6, RCP4.5, RCP6.0 and RCP8.5) (Taylor et al., 2012). RCPs describe four different 21st century pathways of greenhouse gas (GHG) emissions and atmospheric concentrations over time, air pollution and land use. These scenarios include a stringent mitigation scenario (RCP2.6), two intermediate scenarios (RCP4.5 and RCP6.0), and one scenario with very high GHG emissions (RCP8.5) (Allen et al., 2014). However, even though all models can predict the same climate change scenarios, each model delivers significantly different outputs. Assumptions and other model differences produce distinct projections even for the same scenario. In this context, limited efforts have been performed in the building sector towards a comparative analysis of the climate change models used in the last IPCC report to choose and combine the more relevant ones in a new model that better fit the historical data.

In this framework, the paper proposes the analysis of different GCMs based forecasts of climate change. These data are compared with an existing climate database to compare simulated with historical weather data, aimed at generating a new 'data-fusion' dataset through the combination of different IPCC GCMs in order to achieve a new more robust dataset if compared to the real available data to be used for building simulation.

Methods

As shown in Figure 1, the methodological steps followed during the work are recapped below:

- **Models data fusion:** using a multiple linear regression method, four different GCMs are combined into one model (data fusion model) so that the trend of the historical data of the generated model is similar to the data of an historical weather database (ERA-Interim Database);
- **Future hourly weather data:** the data fusion model and also of the four single models are used to construct future climate weather data files for period 2020-2099 using 2 RCP emission scenarios (RCP4.5 and RCP8.5) through the morphing method;
- **Building simulation:** a case study is modelled in EnergyPlus environment in order to assess the effect of the climate change on the building energy use for heating and cooling for the city of Palermo, Italy.

Models Data Fusion

Each GCM includes different types of simulations, such as historical and future projections forced by RCP scenarios. Historical simulations cover much of the industrial period and are guided by the changes observed in the atmospheric composition (both of anthropogenic nature and of natural origin) and by the time-evolving land cover. For future projections, the RCP 4.5 and RCP8.5 scenarios were considered as examples. In particular, RCP 8.5 is a business as usual scenario, with

no policy changes to reduce emissions (three times today's CO₂ emissions by 2100) while RCP4.5 is representative of a "midrange mitigation emission" scenario, where greenhouse gas emissions peak around 2040 and afterwards decline.

In particular, the GCMs showed in Table 1 were used, in a specific location (latitude 38.75°, longitude 13.25°) for the following parameters:

- Tas (Near-Surface Air Temperature [K]);
- sfcWind (wind speed [m/s]);
- Rsds (Surface Downwelling Shortwave Radiation [W/m²]).

Figure 1: Sketch of the methodological framework.

Among all the GCMs recommended by the IPCC in the context of the Fifth Assessment Report, these models were selected because have the same horizontal grid resolution (latitude: 1.25°, longitude: 1.875°), avoiding the need to remap different models to the same spatial grid. Although the proposed methodology could be easily

applied to any set of climatic data, this allows to remove one layer of uncertainty from the results as all data used in this paper use the same spatial grid, removing the need for further manipulation of the data to achieve comparable inputs.

Since these climate variables are characterized by a strong seasonal component which deeply influences the time series, each weather parameter of the GCMs historical simulation was decomposed into a seasonal component, a linear trend and random residual component. Then, for combining the models, each trace was compared with historical weather data provided by the ERA-Interim dataset, in terms of linear trends and variance of the residuals (rather than comparing the sum of errors produced by the temporal traces).

Table 1: Selected GCMs.

GCM	Research centre
ACCESS1.0	Commonwealth Scientific and Industrial Research Organization/Bureau of Meteorology Australia
ACCESS1.3	
HadGEM2-AO	National Institute of Meteorological Research, Korea Meteorological Administration, South Korea
HadGEM2-CC	Met Office Hadley Centre, UK

In detail, ERA-Interim is the last global atmospheric database produced by the European Centre for Medium-Range Weather Forecasts covering the period since 1 January 1979 onwards. It was selected as reference data source because it is an official validation dataset used for the comparison of GCMs (Bojanowski, Vrieling, & Skidmore, 2014; Brands, Herrera, Fernández, & Gutiérrez, 2013; Carvalho, Rocha, Gómez-Gesteira, & Silva Santos, 2017).

To combine the different models into one single model, a multiple linear regression method was used. It is a machine learning technique that “weights” each dataset according to the climatic input data without introducing any additional hypothesis.

In detail, in the linear regression method the output is equal to the sum of a weighted combination of the input, as shown in equation (1).

$$y(w, X) = w_1x_1 + \dots + w_px_p \quad (1)$$

where the vector $w = (w_1, \dots, w_p)$ contains the coefficients (regression weights) of the inputs $X = (x_1, \dots, x_p)$, while y is the output linear combination.

The regression weights were selected in order to minimize the difference between the output linear combination y and the historical data from the ERA-Interim database (Dee et al., 2011). The obtained regression weights allow to combine linearly the four selected GCMs and obtain a unified model, spanning the same time period, for each climatic parameter considered. The regression weights have been obtained using historical data from years 1979–2000 that overlap on the ERA-Interim period, for the climate parameters tas , $sfcWind$ and $rsds$, in the Palermo, Italy area (Latitude 38.75°, Longitude 13.125°).

In order to obtain the regression weights, a simple solution is to use the Least Square Error method that minimizes the MSE (Mean Square Error), or the standardized version of the MSE, namely the coefficient of determination R^2 .

This approach, although valid in many cases, is based on the assumption that the different inputs of the model are independent. However, when the inputs are correlated and the columns of the X matrix have a quasi-linear dependence (as in this case), the method becomes highly sensitive to the random fluctuations of the response, producing a large variance that makes the values of the coefficients w not reliable.

To overcome this problem, the Elastic-Net regression method was used (Zou & Hastie, 2005). It is a more sophisticated linear regression model trained with two regularization parameters, α and ρ . Its objective function to be minimized can be expressed mathematically in the following form:

$$\min_w \frac{1}{2n_{samples}} \|Xw - y\|_2^2 + \alpha \rho \|w\|_1 + \frac{\alpha(1-\rho)}{2} \|w\|_2^2 \quad (2)$$

The combined action of α and ρ keeps the amplitude of the coefficients low and at the same time tries to guarantee a certain “sparsity” of the coefficients. The appropriate choice of these parameters is a useful way to reduce the risk of overfitting.

The regularization parameters α and ρ were identified through the cross-validation mechanism with grid search using the ElasticNetCV classifier of the scikit-learn Python library for machine learning (Pedregosa et al., 2011). More detailed information on how we implement and use the ElasticNetCV regression can be found in (F. Guarino, Inzerillo, Croce, Tinnirello & Cellura, 2018). Tables 2 and 3 show the regularization parameters and the regression weights obtained, respectively.

Table 2: Regularization parameters obtained for the three parameters of interest.

	α	ρ
Tas	10	0.001
SfcWind	0.001	0.75
RSDS	10	0.5

Table 3: Regression weights obtained through the Elastic-Net.

	w_1	w_2	w_3	w_4
Tas	0.386	0.371	0.182	0.061
SfcWind	0.153	0.477	0.122	0.173
RSDS	0.422	0.139	0.408	0.055

Table 4 shows the MSE and R^2 coefficient for the resulting data fusion model and of the four single models compared to the ERA-Interim dataset. In detail, for all the climatic variables considered, the data fusion model shows a higher R^2 coefficient and a lower MSE if compared to the individual GCMs, resulting in a model that better fit historical data of ERA-Interim database.

Finally, the weights coefficients obtained on the historical datasets through the Elastic-Net method were used to

obtain a unified future forecast model based on the RCP4.5 and RCP8.5 scenarios.

Table 4: MSE and R² coefficient of selected GCMs compared to the ERA Interim dataset.

	Tas [K]		SfcWind [m/s]		Rsds [W/m ²]	
	MSE	R ²	MSE	R ²	MSE	R ²
ACCESS1.0	3.14	0.87	1.05	0.44	310.68	0.96
ACCESS1.3	2.67	0.89	1.47	0.21	411.42	0.94
HadGEM2-AO	2.32	0.90	1.56	0.17	367.39	0.95
HadGEM2-CC	3.20	0.87	1.89	-0.01	359.08	0.95
Data fusion model	2.17	0.91	0.72	0.62	262.78	0.96

Future hourly weather data

The results achieved from the previous step were used for development of weather data files to be used for simulation of future energy performances in a non-steady state simulation environment.

Both the original climate data from the 4 GCMs and the data-fusion results were used for the generation of hourly weather data file for the period 2020-2090 through the application of the “morphing method” proposed by (Belcher et al., 2005) allowing to modify a hourly weather data for the desired site on the basis of forecasted factors and disturbances to climate.

The morphing method (Belcher et al., 2005) is based on three operations, which can be described as: shift (equation (3)); linear stretch (equation (4)); shift and stretch (equation (5)).

$$z = z_0 + \Delta z_m \quad (3)$$

$$z = \alpha_m z_0 \quad (4)$$

$$z = z_0 + \Delta z_m + \alpha_m (z_0 - \langle z_0 \rangle) \quad (5)$$

where the subscripts “0” identify current weather variables, while the subscripts “m” identify monthly future weather data. In detail, z is a future hourly climate variable, z_0 is the hourly value of the current climate variable, Δz_m and α_m are the absolute variation and the percentage variation of said climate variable due to climate change for month m , respectively, and $\langle z_0 \rangle$ is the monthly mean of the variable z_0 .

This method was used because it is one of the most used in researches on the impact of climate change on building energy use in the U.S.A (L. Wang, Liu, & Brown, 2017), in Canada (Robert & Kummert, 2012), in Australia (Ren, Chen, & Wang, 2011), in Asia (Song & Ye, 2017) and in Europe (Maurizio Cellura, Guarino, Longo, & Tumminia, 2018) using as input different GCMs, climate change scenarios and future time slices.

The IWECC (International Weather for Energy Calculation) EPW weather file format (Thevenard & Brunger, 2002) for the city of Palermo was selected as the baseline weather data in input to the morphing method because it is one of the most widely weather formats used by energy building simulation tools.

Building simulation

An ideal building model was modelled in EnergyPlus environment (DoE, 2010). The building performances have been analysed with a sub-hourly detail (10 min time step) by using the conduction transfer function method for the envelope and the heat balance method to analyse the thermal zones.

As shown in Figure 2, a multi-storey building model was used as ideal case study with a total heated area of 400 m². An isolated building was chosen to adopt the worst conditions for cooling since climate change will most likely increase this typology of energy use in the future (S Ferrari & Zanotto, 2016).

Figure 2: The building model used as case study.

The building is an office occupied from Monday to Friday from 9:00 a.m. until 6:00 p.m., with a break for lunch from 1:00 p.m. to 2:00 p.m. Table 5 reports the main buildings features. In particular, the window-to-wall ratio of all façades is about 30%, with about 36 m² of glazed area (Goia, 2016).

Table 5: Building features.

Heated Floor area [m ²]	400
Volume [m ³]	1,200
S/V overall ratio [m ⁻¹]	0.48
Window to wall ratio [%]	30

Since the typical lifetime of buildings is in the range of 50–100 years and in order to ensure representativeness of the building modelled, the building envelope features are chosen in compliance with the minimum requirements for a new non-residential building in force for the city examined, Palermo (Italy) (Ministero dello Sviluppo Economico, 2015).

The windows are made of a double panel insulated glazing, the average global window U-value is 2.83 W/(m²K), while the Solar Heat Gain Coefficient is 0.49. U-value for vertical surfaces is 0.40 W/(m²K), 0.32 W/(m²K) for the roof and 0.42 W/(m²K) for the floor. All walls have an internal mass layer (brick, 30 cm for external walls) and external insulation (5 cm for the walls and 9 cm for the roof).

Thermal internal loads are caused by lighting and office equipment. Lighting power installed is 5 W/m², controlled by an illuminance dimming with a setpoint of 500 lux activated by the presence of people inside the building.

Other electrical loads are included: computers with monitors and a printer, overall 30 W/m² installed (BRECSU, 2000; CIBSE, 2012).

Natural ventilation is modelled through the separate contributions of wind and stack to the airflow through the Wind and stack empiric formulation (American Society of Heating & Air-Conditioning, 2005; Guarino et al., 2016): wind induced ventilation is obtainable through equation (6), while the equation (7) is used for calculating the ventilation rate due to stack effect:

$$Q_w = C_o A_{opening} W_s \quad (6)$$

$$Q_s = C_D A_{opening} \sqrt{2g \Delta H_{NPL} (|T_z - T_o| / T_o)} \quad (7)$$

Where C_o is the opening effectiveness, A is the opening area [m²], W_s is the wind speed, C_D is the Discharge coefficient for opening, ΔH_{NPL} is the height from midpoint of lower opening to the neutral pressure level [m], T_z and T_o are respectively the temperature of the zone and the outdoor one [°C]. Windows are open when external air temperature is in the range of $18 < T_o < 26$ °C, internal temperature is below 23°C and wind speed is lower than 2 m/s.

Finally, to cover the heating and cooling demand an ideal loads air systems using 20 °C and 26 °C as heating and cooling set-points was used, with a coefficient of performance and an energy efficiency ratio of around 3.2 and 3, respectively. This choice is based on the difficulty to quantify potential energy efficiency improvements in HVAC systems up to 2099 and to be able to perform a solid comparison between all results in all scenarios.

Results

In this section, based on the assumptions made in the previous section and based on the assumptions of the latest IPCC future climate projections, results on the future climate projections and the potential impact of climate change on the energy uses for heating and cooling for the city of Palermo are presented.

Results on future climate projections

Figure 3 shows the yearly mean dry bulb temperature for the future period 2020-2099 in the case of RCP4.5 and RCP8.5 scenarios.

For both scenarios, the yearly mean dry-bulb temperature is expected to increase. In particular, considering the RCP4.5 scenario for the year 2099, the results show that the yearly temperature increase is expected to be between 2.4 °C (ACCESS1.3) and 3.3 °C (HadGEM2-CC) compared to the mean yearly temperature of the current situation (18.8 °C). On the other hand, the results for the year 2099 under the scenario RCP8.5 show that the model ACCESS1.3 is the model that foresees the greatest increase in yearly temperature (+5 °C) while the HadGEM2-AO is characterized by the lowest increase for the city of Palermo (+4.5 °C).

The distribution of the results among the five GCMs shows some differences between the models. Considering the scenario RCP4.5 (Figure 3a), the model ACCESS 1.3 proposes the most extreme weather forecasts (for about

50% of the time in the period between 2020 and 2099, this model shows the highest mean annual temperatures), while the model ACCESS 1.0 shows the most temperate one. The results for the scenario RCP8.5 (Figure 3b) show that the model HadGEM2-AO foresees the greatest increase in yearly temperature (for about 46% of the time in the future period considered, this model shows the higher mean yearly temperatures if compared to the other GCMs). Finally, for both scenarios, the Data fusion model always shows intermediate results between all models investigated.

Figure 3: Future yearly average values of dry-bulb temperature under the RCP4.5 and RCP8.5 scenarios.

Results of building simulation

The case study was simulated for the current situation (i.e. the energy simulation was run using the IWEC weather file for the city of Palermo, that covers the period 1982-1999) and for the two different future scenarios, each with all climate data models mentioned in the previous sections as well as with the Data fusion model.

Table 6 shows the monthly electricity energy demand for heating and cooling for the current situation. Due to a mild climate, high internal thermal loads and large glazed facades, the yearly heating energy demand (around 5.5 kWh_e/(m²year)) is lower than the cooling demand (about 13.5 kWh_e/(m²year)). In detail, the months that need more heating are January (1.8 kWh_e/m²) and February (1.6 kWh_e/m²), while the months of July and August require

the highest cooling demand, respectively 4.4 kWh/m² and 5.5 kWh/m².

Table 6: Heating and cooling energy demand for the current situation.

	Heating energy demand [kWh/m ²]	Cooling energy demand [kWh/m ²]
Jan	1.75	0
Feb	1.64	0
Mar	0.54	0
Apr	0.13	0.07
May	0	0.18
Jun	0	1.29
Jul	0	4.35
Aug	0	5.47
Sep	0	1.51
Oct	0	0.64
Nov	0.23	0.02
Dec	1.21	0
Tot	5.50	13.53

Figure 4 shows the yearly electricity energy demand for cooling and heating for the future forecast period 2020-2099 in the two RCP scenarios. Rises in the yearly cooling energy use and decrease in heating energy use are found due to the outdoor dry-bulb temperature increase brought

by the climate change, but the magnitude of the change varies for different climate change scenarios.

Although in the current situation, the heating energy demand accounts for roughly the 30% of the total energy uses for air conditioning, this is not the case anymore for the future scenarios. For example, considering the future projection for the year 2099, the cooling energy demand is nearly increased by 50% in the RCP 4.5 scenario whereas the heating energy demand (Figure 4c) is reduced to a third. On the other hand, in the RCP8.5 scenario the heating energy demand (Figure 4b) is close to zero while the cooling energy demand (Figure 4d) is increased threefold.

As per the previous results on the future climate projections, also the results on the cooling and heating energy demand are very sensitive to choice of the GCM.

In detail, the results on the heating energy demand show highest differences among the models, while considering the cooling energy demand, for both scenarios the results are more uniform between the different models. For example, considering the cooling energy demand for the scenario RCP4.5, results can vary as much as 35% (year 2095) with a mean variation in the period 2020-2099 of about 17%, merely by using one data source to another.

In this context, the Data fusion model (red bold line in Figure 4) always shows middle results between all GCMs investigated.

Figure 4: Future heating and cooling energy demand under the RCP4.5 and RCP8.5 scenarios.

Discussions and conclusions

A range of uncertainties linked to predicted energy demand changes for buildings under projected future

weathers is due to the availability of different climate models used, reinforcing the need for careful assessment of the available GCMs for any specific location when

developing specific building designs. In this context, the paper proposes the analysis of four different climate models approved from the IPCC, showing a wide variability among the future climate forecast of the different models. Within two RCP scenario (RCP4.5 and RCP8.5), results from a climate analysis indicate that this range can have a large impact on the predicted energy consumption of the building sector.

For example, considering the cooling energy demand for the scenario RCP8.5, by using data from one climate model rather than another, results can vary as much as 31% (year 2046), while considering the scenario RCP4.5 the maximum variation in the cooling energy requirements is equal to about 35% (year 2095). Therefore, so large variations in predicting the future energy demands of the building sector could have relevant impacts in terms of costs, decarbonisation potential and environmental impacts of this sector.

In this context, this research presented a methodology to integrate different climate change models data into a new 'data-fusion' model, in order to achieve a new more robust dataset if compared to the real available data.

The approach presented in this paper can help local decision makers and local utilities make more informed decisions regarding future policies and business choices. The paper is also aimed towards buildings designers and practitioners of non steady-state building simulation, since the evolution of predicting weather data for the next decades is one of the research challenges of the years to come and one to impact the building modelling and simulation in the next decades.

The same process can be applied to other locations throughout the world, which can help in making informed decisions regarding building standards, energy management and emission policies.

Furthermore, the generation of building simulation weather files allowed for the quantification of potential significant differences between different models outputs, strengthening the need for a more detailed approach to climate change modelling.

Finally, the research also presented the usage of climate-changed weather data by performing an energy analysis based on building simulation suggesting that future global warming will have a significant impact on building energy performances. In detail, the results show, in both RCP scenarios considered, consistent and large increases in future air temperature. In this context, in order to try and avoid potentially much larger issues in the future, there is a need for tools and methods that allow to include climate change as one of the variables to be taken into consideration during the design stage for both the construction of the new buildings and the retrofit of the existing stock.

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