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Climate change: Projections and implications to building energy use

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Research Article

Abstract

Changes in climate have significant impacts on built environment. Many of the potential effects of climate change on the building sector are not well known. Previous studies have used a small number of climate projection models and scenarios, with the majority only using one or two models with multiple scenarios. This study identified and analyzed twenty-three climate models with one or more scenario for each model for total of fifty-six model scenarios. Future hourly weather data between 2011 and 2099 was generated with the morphing algorithm for seven climate zones in the US. Using cooling degree day (CDD) and heating degree day (HDD) as energy impact indicators, the study revealed that different climate models (even within the same RCP scenario) yield largely different results for building energy implications. To simplify application, four reference climate models were selected to represent the full range of the fifty-six model outputs, whose accuracy was validated using historical data. The study explored the impacts of climate changes on energy use of five typical US building types in Ann Arbor, MI, as a demonstration, which presented a general trend of site energy decrease and source energy increase for this location. The research further examined the influences of humidity and found that dry bulb temperature dominates the changes in building energy consumption and relative humidity only has a relatively larger impact on extreme cases in cooling dominated climates.

Keywords

climate change,
projection,
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1 Introduction

Climate change is widely acknowledged a major environmental problem facing the planet. The Intergovernmental Panel on Climate Change (IPCC) estimated that between 1970 and 2004, global greenhouse gas emissions rose 70% (IPCC 2014). The impacts due to climate change are not fully understood; however, it is agreed by most that the world will see weather changes that will have a significant impact on all aspects of our lives. Evidence indicates that the effects of climate change include elevated temperatures, rising sea levels, heavier precipitation events, additional heat waves, and more areas affected by drought (IPCC 2014). The level of impacts will vary by region. Different continents will see different changes depending on their geography and location. Within each continent there will be varying effects and vulnerabilities depending on location (Huovila 2007).

Many of the effects of the building sector on climate change are well known. The building sector contributes up to 30% of global annual greenhouse gas emissions and consumes up to 40% of all energy (IPCC 2007). Furthermore, between 1971 and 2004, carbon emission is estimated to have grown at a rate of 2.5% per year for commercial buildings and at 1.7% per year for residential buildings (Levine et al. 2007). However, many of the potential effects of climate change on the building sector are not well known. Changes in climate will have significant impacts on built environment, and it will be crucial to understand these effects.

Climate models have been developed and used to project climate changes, upon a standard set of greenhouse gas scenarios called Representative Concentration Pathways (RCPs) used in the IPCC Fifth Assessment Report (AR5). RCPs describe four different 21st century pathways of Greenhouse Gas (GHG) emissions and atmospheric concentrations, air pollution and land use. They 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) (IPCC 2014). For each category of emissions, an RCP contains a set of starting values and the estimated emissions up to 2100, based on

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assumptions about economic activity, energy sources, population growth, and other socio-economic factors (IPCC 2014). The four RCPs, RCP2.6, RCP4.5, RCP6, and RCP8.5, are named after a possible range of radiative forcing values in the year 2100 relative to pre-industrial values (+2.6, +4.5, +6.0, and +8.5 W/m^2, respectively). Table 1 shows the four climate change scenarios and their resulting surface temperature changes and sea level rises (IPCC 2014). As indicated, the trend is clear that the global temperatures will rise. It is just a matter of how much. It is important to note that this trend is global. Regional trends may differ (Huovila 2007).

Quantifying how these changes may affect the building sector, and specifically building energy use will be important. One major area directly affected by climate change will be heating and cooling energy (Department of Ecology 2012). About 50% of building energy consumption is due to space heating and cooling (US Department of Energy 2011). As outdoor temperature and humidity levels change, the energy profiles of built environment will also change (Department of Ecology 2012). By understanding and predicting these changes, people can better build and design structures so that they can combat potential problems associated with climate change.

The first step in understanding the effects of climate change on building energy consumption is to better understand climate change models and scenarios. Weather and climate models have many things in common, including tendencies for error (Oregon Climate Change Research Institute 2010). Human's knowledge of the future is not perfect. For example, future greenhouse gas concentrations depend on future releases, which are ultimately unknown (Oregon Climate Change Research Institute 2010). For these reasons of uncertainty, it is important to examine as many climate change scenarios as possible in order to get a broader understanding of potential effects on building energy use. Once the potential impacts of climate change on the built environment are understood, one can begin to implement adaptation strategies including the implementation of new design strategies and technologies as well as the changes in operation and use (Cooper 2010).

2 Review on building energy implications of climate changes

A few methods exist to analyze implications of climate change on building energy use. In early studies a simple degree day based method was used (Wang and Chen 2014). The main principle of this method is that the building energy use is proportional to the heating and cooling degree days for the location of the building. The degree day analysis uses the balance point temperature of a building, which is the temperature at which the building does not require heating or cooling. The balance point temperature varies by building and location. The heating degree days (HDD) and cooling degree days (CDD) are calculated hourly over a year using Eqs. (1) and (2) (Cooper 2010).

$$\mathrm{HDD} = \sum^{365}\sum^{24}(T_{\mathrm{b}} - T_{\mathrm{o}})^{+}/24 \qquad (1)$$

$$\mathrm{CDD} = \sum^{365}\sum^{24}(T_{\mathrm{o}} - T_{\mathrm{b}})^{+}/24 \qquad (2)$$

where T_{b} is the balance point temperature and T_{o} is the outdoor hourly temperature. The plus sign shows that only positive values will be used (Wang and Chen 2014). This method can provide an estimate of the impact of climate change (if future outdoor temperature is used) on buildings. However, this approach only accounts for sensible load because merely the dry bulb temperature is taken into consideration. Solar radiation, humidity and other building characteristics are not considered.

Rosenthal et al. (1995) used the degree day method to study the effect of climate change on residential and com-

Table 1 Summary of IPCC predicted climate change scenarios (IPCC 2014)

		2046–2065		2081–2100	
	Scenario	Mean	*Likely* range	Mean	*Likely* range
Global mean surface temperature change (°C)	RCP2.6	1.0	0.4 to 1.6	1.0	0.3 to 1.7
	RCP4.5	1.4	0.9 to 2.0	1.8	1.1 to 2.6
	RCP6.0	1.3	0.8 to 1.8	2.2	1.4 to 3.1
	RCP8.5	2.0	1.4 to 2.6	3.7	2.6 to 4.8
	Scenario	Mean	*Likely* range	Mean	*Likely* range
Global mean sea level rise (m)	RCP2.6	0.24	1.17 to 0.32	0.40	0.26 to 0.55
	RCP4.5	0.26	0.19 to 0.33	0.47	0.32 to 0.63
	RCP6.0	0.25	0.18 to 0.32	0.48	0.33 to 0.63
	RCP8.5	0.30	0.22 to 0.38	0.63	0.45 to 0.82

mercial buildings in the US. They concluded that a 1 °C increase in outdoor temperature will reduce energy costs for the US building stock by $5.5 billion. Amato et al. (2005) also applied a degree day method in studying residential and commercial buildings in Massachusetts. Based on CGCM1 and HadCM2 climate change model outputs, they concluded that climate changes would result in a 1.2%–2.1% increase in electricity and a 7%–14% decrease in natural gas consumption. Olonscheck et al. (2011) employed the degree day method to study residential buildings in Germany. Based on a 1–3°C temperature increase, they found a 44%–75% decrease in heating and a 28%–59% increase in cooling.

The degree day method is extremely simplified and results could potentially have a large error. Hour by hour building energy simulation is a better approach for studying the impacts of climate change on building energy use (Cooper 2010). Energy modeling is a more accurate and widely used method to analyze effects of climate change on a building or building stock. In this method, an energy modeling program such as EnergyPlus or eQUEST is employed to predict the effect of climate change using a future weather file. Using one or more of the climate change models, weather data can be adjusted so that it can represent typical weather for a future time period.

Multiple studies have been performed using morphing as a downscaling technique for energy modeling. Most of these studies used only several climate change models. Chan (2011) applied this technique to study apartment and office buildings in Hong Kong. Based on MICRO3_2_MED weather projection, they concluded a 1.6%–14.3% increase in A/C energy use for office buildings and a 3.7%–24% increase in residential A/C energy use. Huang et al. (2009) studied commercial buildings in California. Based on HadCM3 for weather projection, they concluded that there would be a 50% increase in cooling electricity by 2100 and a 25% increase in peak cooling. Wang et al. (2010) used 9 Global Circulation Models (GCMs) to study residential buildings in 5 regions of Australia. Based on the 9 GCMs they predicted a range in energy change by 2100 of −48% to 350%. Wang and Chen (2014) also studied the impacts of climate change on various types of residential and commercial buildings in all seven climate zones in the US. They concluded that there would be a net increase in source energy consumption by the 2080s for climate zones 1–4 and a net decrease for zones 6–7 based on HadCM3 weather projections.

Recently, Shen (2017) integrated one GCM to the typical meteorological year weather file to predict local hourly weather data in the US using a morphing methodology. Case studies in four representative cities in the US showed that the change of annual energy use is predicted to range from −1.64% to 14.07% for residential building and from −3.27% to −0.12% for office building under A2 scenario in different regions in 2040–2069. The research suggested that the climate change will narrow the gap of energy use for residential buildings located in cold and hot climate regions in the US and generally reduce office building energy use in the future. It was also found that the energy use of lightings and fans will slightly decrease in the future, but the growing peak electricity load during cooling seasons is going to exert greater pressure for the future grid. Cao et al. (2017) investigated the effects of climate change on building energy-saving design in the different climate zones of China and found that the increasing rate of design temperatures for both heating and air-conditioning in winter were in the range of 0.2 –0.7 °C/decade, and the rate of design temperature for air-conditioning in summer was in the range of 0.1 –0.4 °C/decade. Angeles et al. (2018) assessed the impacts of climate change on building energy demands in the intra-Americas region using the Intergovernmental Panel on Climate Change (IPCC) Representative Concentration Pathways (RCP) 2.6 and 4.5 scenarios and forecasted an increase of 9.6 and 23 kWh/month, respectively by the end of the twenty-first century, which may increase average building cooling loads in the region by 7.57 GW (RCP2.6) and 8.15 GW (RCP4.5), respectively.

Aijazi and Brager (2018) presented an overview and a case study to demonstrate how climate change impacts on building can be simulated and will vary by building type and location. It is generally agreed that the climate change impact on energy demand is sensitive to building type and location. Huang and Gurney (2016) predicted that the warehouse showed an increase of >100% energy consumption at some summer hours while the secondary school building showed an increase of >39% energy consumption in August. Cellura et al. (2018) used a GCM data to model the energy implications to an office building in Southern Europe that shows the increase in air temperature in South EU up to 9 °C and the cooling energy cooling increase up to 120% in 2090. Pérez-Andreu et al. (2018) predicted the impacts of climate change on heating and cooling energy demand in a residential building in a Mediterranean climate with two GCMs for 2050 and 2100. The study indicated that heating energy demand decreases significantly, and cooling energy demand increases. They suggested thermal insulation and infiltration have the greatest effect on total energy demand.

The literature review reveals a wide range of predicted energy demand changes for buildings under projected future weathers due to different building types, locations, building models, and climate models used. Although general trends were observed as commonly sensed, some contradictive conclusions were presented. Most of the previous studies used few climate models to predict the influences of climate changes on several typical building models. This indicates a need for a more comprehensive study that utilizes and analyzes a larger number of energy models and scenarios. Most studies predate AR5 so the models and scenarios that were used have since been upgraded. The AR5 covers a larger range of scenarios than the Special Report on Emissions Scenarios (SRES) used in previous assessments (IPCC 2014). When comparing the AR5 scenarios to the previous SRES scenarios, 3 of the 4 have an equivalent scenario. However, the RCP2.6 has no equivalent, therefore there will be a difference in magnitude of the SRES and AR5 climate projections due to a wider range of emissions scenarios (IPCC 2014). Using a large number of AR5 projections will allow a better estimate on the range of how climate change will affect a particular building or building stock.

Furthermore, multiple improvements have been made to the climate models since the AR4 (IPCC 2014). The AR5 models reflect an improved understanding of how climate processes work. Despite the progress, scientific uncertainty still exists within the models. Some models perform better than others for certain climate variables, but no individual model clearly emerges as "the best" overall. For this study, the climate variable in consideration is mean surface air temperature (TAS) (IPCC 2014). AR5 reports that the confidence for the TAS projection is high. There is robust evidence of improvement in the TAS prediction since the last IPCC Assessment Report (AR4) (IPCC 2014). All these justify the necessity and importance of this research.

3 Climate models

3.1 Overview

When studying any topic related to climate change, a key challenge is reliability of climate models. The IPCC has approved and recommended a number of climate change models. These models are a mathematical representation of the interaction between and within the ocean, land, ice and atmosphere. Each of these components is distinct within the model. The components are divided spatially into a set of boxes. The movement of energy, air and water are represented as horizontal and vertical exchanges between the boxes based on fundamental equations. The computing power for these simulations is immense, so some of the world's largest super computers in the world are used for these models. Specific details of all IPCC climate change models can be found in Appendix 9.A of the AR5 (IPCC 2014).

The IPCC approved climate change models all show a similar trend; however, they still vary immensely. Accurately predicting climate change is huge barrier in fully understanding how climate change will affect the built environment (Oregon Climate Change Research Institute 2010). Another challenge is generating an accurate representation of future weather with a small time step. For building energy simulation models, hourly data for one year is needed. Climate change data is usually given in years because as the time step gets smaller accuracy decreases. Many IPCC climate change models report monthly climate data; but this data has a higher uncertainty. In order to use building energy models, the monthly data must be transformed into hourly data, which provides even more uncertainty. Lastly, it is unclear whether using a larger number of climate models will more accurately represent the range of climate change effects on a building or building stock. Studies in literature often use a small number of climate models, without adequate justification of which models may provide a more accurate representation of future climate changes.

One of the largest challenges in modeling climate change is the accuracy of the climate models as discussed earlier. Figure 1 shows relative error measures of climate model performance, based on the global seasonal cycle climatology (1980–2005) computed from historical experiments (IPCC 2014). A space-time root-mean-square error (RMSE) is used to present the error for each variable and model. Rows and columns are represented by the models and variables. The value corresponds to the relative error by normalizing the result by the median error of all model results. For example, a value of 0.1 indicates that one model's RMSE is 10% larger than the median climate model error for that variable (IPCC 2014). The diagonal split shows the relative error with respect to both the default reference data set and the alternate. The climate variable of importance for building energy prediction is surface air temperature (TAS) that can be seen in the column on the left-hand side of Fig. 1 (IPCC 2014). The TAS error is thus used in choosing the suitable models for further test. Models such as the IPSL-CM5B-LR and the GISS-E2-H are left out due to high error. Models that show a relatively low error and are available in the data

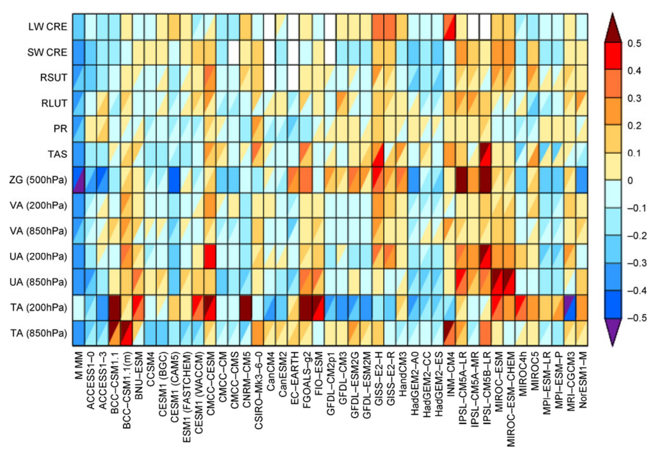

Fig. 1 Error in variable prediction (Y) for various climate models (X) (IPCC 2014)

library are chosen for further investigation. The scenarios for each model are chosen strictly based on their data availability within the model.

Although all models are predicting the same four climate change scenarios (4 RCPs), each model provides a great number of differences. Assumptions and other model differences produce different projections even for the same RCP scenario. As a result, using a larger sample size in model and scenario will provide a larger range of possibilities. All previous studies have used a small number of models and scenarios, with the majority only using one model with multiple scenarios. This study uses 23 models with one or more scenario for each model for total of 56 model scenarios. All models used are a part of a suite of climate models approved by the IPCC. A list of models and corresponding scenarios used can be seen in Table 2. These model scenario projections are made available by the Archive Collaborators (i.e., Bureau of Reclamation, Climate Analytics Group, Climate Central, Lawrence Livermore National Laboratory, Santa Clara University, Scripps Institution of Oceanography, US Army Corps of Engineers, US Geological Survey, and National Center for Atmospheric Research) (https://gdo-dcp.ucllnl.org/downscaled_cmip_projections/dcpInterface.html).

3.2 Baseline and projected weather data

The baseline climate data is defined as the current weather sequence averaged over a number of years. The World Meteorological Organization recommends using an averaging period of 30 years to define the current climate baseline (Belcher et al. 2005). The climate data projections provide monthly projections from the year 1950 to 2100. This study uses a baseline period of 1970–1999. The model simulations from this period provide the baseline data for predicting the future scenarios. Therefore, the projected change in climate

Table 2 List of selected climate models and scenarios

Model name	Institution	Scenarios
ACCESS1.0	Commonwealth Scientific and Industrial Research Organization (CSIRO) and Bureau of Meteorology (BOM)	RCP4.5
BCC-CSM1.1	Beijing Climate Center, China Meteorological Administration	RCP2.6, RCP4.5, RCP6.0, RCP8.5
CanESM2	Canadian Center for Climate Modelling and Analysis	RCP2.6
CCSM4	US National Center for Atmospheric Research	RCP2.6, RCP4.5, RCP6.0, RCP8.5
CESM1 (CAM5)	NFS-DOE-NCAR	RCP2.6, RCP4.5, RCP6.0, RCP8.5
CMCC-CM	Centro Euro-Mediteraneo per I Cambiamenti Climatici	RCP8.O
CNRM-CM5	Centre National de Recherches Meteorologiques and Centre Europeen de Recherche et Formation Avancees en Calcul Scientifique	RCP4.5
CSIRO-Mk3.6.0	Queensland Climate Change Centre of Excellence and Commonwealth Scientific and Industrial Research Organization	RCP2.6, RCP4.5, RCP6.0, RCP8.5
EC-EARTH	Europe	RCP2.6
FGOALS-g2	LASG (Institute of Atmospheric Physics)-CESS (Tsinghua University)	RCP2.6
FIO-ESM v1.0	The First Institute of Oceanography, State Oceanic Administration, China	RCP2.6, RCP4.5, RCP6.0, RCP8.5
GFDL-CM3	NOAA Geophysical Fluid Dynamics Laboratory	RCP6.0
GFDL-ESM2M	NOAA Geophysical Fluid Dynamics Laboratory	RCP2.6, RCP4.5, RCP6.0, RCP8.O
GISS-E2-R	NASA Goddard Institute for Space Studies USA	RCP2.6, RCP4.5, RCP6.0, RCP8.5
HadGEM2-AO	National Institute of Meteorological Research/Korea Meteorological Administration	RCP6.0
HadGEM2-ES	UK Met Office Hadley Centre	RCP2.6, RCP4.5, RCP6.0, RCP8.5
INM-CM4	Russian Institute for Numerical Mathematics	RCP4.5
IPSL-CM5A-LR	Institut Pierre Simon Leplace	RCP6.0
IPSL-CM5A-MR	Institut Pierre Simon Leplace	RCP2.6, RCP4.5, RCP6.0, RCP8.5
MICROC5	University of Tokyo, National Institute for Environmental Studies, and Japan Agency for Marine Earth Science and Technology	RCP2.6, RCP4.5, RCP6.0, RCP8.5
MPI-ESM-MR	Max Planck Institute for Meteorology	RCP8.5
MRI-CGCM3	Meteorological Research Institute	RCP8.5
NorESM1-M	Norwegian Climate Centre	RCP2.6, RCP4.5, RCP6.0, RCP8.5

variable will be the difference between the simulated future climate scenario and the simulated base scenario (Belcher et al. 2005).

The projected years from 2011 to 2099 are broken up into three time periods of 30 years: 2011–2039, 2040–2069, and 2070–2099. These three time periods are referred to as Period 1, Period 2 and Period 3, respectively. Monthly data is averaged for each of these three future periods and compared to the baseline average in order to calculate the projected change in climate variable. These changes are then applied to the morphing algorithm that will generate hourly data. This results in three climate profiles for each model scenario representing the three time periods until the year 2100.

4 Data processing and analysis of climate models

4.1 The morphing algorithm

The Morphing Algorithm is one of the most widely used and most accurate method to downscale monthly data to an hourly profile, and is thus employed here to develop hourly data that can be further used in building energy simulation. The governing equations for the Morphing Algorithm can be found below in Eqs. (3)–(5) (Olonscheck et al. 2011):

$$x = x_o + \Delta x_m \tag{3}$$

$$x = \alpha_m x_o \tag{4}$$

$$x = x_o + \Delta x_m + \alpha_m \times [x_o - (x_o)_m] \tag{5}$$

where the predicted hourly x is based on the present hourly x_o, Δx_m is the absolute change in monthly mean climatic variable, α_m is the fractional change in monthly climatic variable. The three equations, respectively, represent a shift in variable, a stretch in variable and a combination, to accurately modify the weather data (Belcher et al. 2005). This method was validated by Jentsch et al. (2008).

This study uses three variables from the outputs of the climate models: average monthly surface air temperature (TAS), minimum monthly surface air temperature (TASmin), and maximum monthly surface air temperature (TASmax). These variables are applied to the Morphing Algorithm. Although there will be changes in all climatic variable such as relative humidity (RH) and pressure, they are held constant in the current study. Dew point temperature is calculated using the new calculated dry bulb temperature (dbt) in order to ensure that the weather file is psychometrically accurate. A sensitivity analysis of relative humidity is performed later to show its possible effects. For calculation of the dry bulb temperature, the following morphing equation is used (Belcher et al. 2005).

$$\mathrm{dbt} = \mathrm{dbt}_o + \Delta\mathrm{Temp}_m + \mathrm{adbt}_m \times [\mathrm{dbt}_o - (\mathrm{dbt}_o)_m] \tag{6}$$

Hourly predicted dry bulb temperature (dbt) is based on an hourly profile from present day weather data (dbt_o). This study uses the typical meteorological year (TMY) data. $(\mathrm{dbt}_o)_m$ is the monthly mean temperature in the existing TMY data. $\Delta\mathrm{Temp}_m$ is the predicted change in monthly mean dbt and provides the shift for the Morphing Algorithm. The stretch term adbt_m is calculated using Eq. (7) (Belcher et al. 2005).

$$\mathrm{adbt}_m = \frac{\Delta\mathrm{Tmax}_m - \Delta\mathrm{Tmin}_m}{(\mathrm{dbt}_{omax})_m - (\mathrm{dbt}_{omin})_m} \tag{7}$$

where $(\mathrm{dbt}_{omax})_m$ and $(\mathrm{dbt}_{omin})_m$ represent the monthly mean daily maximum and minimum temperature from each month in the existing TMY data. $\Delta\mathrm{Tmax}_m$ and $\Delta\mathrm{Tmin}_m$ represent the predicted changes of monthly maximum and minimum temperature (Zhu et al. 2013).

4.2 Data processing program

A data processing program has been developed using both Microsoft Excel and Matlab, which can be used to create future hourly weather files compatible with building energy modeling programs. The program imports two sets of data, the raw TMY data and the climate model data. The climate data needed is monthly data for 3 climate variables: average monthly temperature, average daily maximum temperature, and average daily minimum temperature. The TMY data needed is hourly dry bulb temperature. The Morphing Algorithm is then coded to generate and export the future hourly profiles in Excel format for further processing, such as calculating all necessary psychometric parameters and producing epw weather file for EnergyPlus software. The final output from this process is a future weather file for any RCP scenario and time period chosen.

4.3 Scenario analysis

This study uses a large number of model scenarios; therefore, it is necessary to analyze and compare the profiles generated by each model scenario. The profiles are first separated into their individual RCP scenario. Each RCP scenario contains 14 model profiles (as seen in Table 2). Afterwards, a statistical analysis is conducted to analyze major differences between models within the same scenario group.

Using 56 model scenarios adds an extra level of rigor but also sophistication to an analysis. The study thus tries to find a set of 4 reference models that can provide a similar range of climate change effects to the 56 model scenarios. This is carried out by analyzing the 56 projected hourly profiles for 7 representative climate zones in the US. The American Society of Heating, Refrigerating, and Air-Conditioning Engineers (ASHRAE) defines 16 different climate zones based on cooling degree day (CDD), heating degree day (HDD), and precipitation. The 16 zones are separated into climate zones 1 through 8 depending on the number of annual HDD or CDD. Each zone also has a corresponding subtype A, B, or C (ANSI/ASHRAE/IES 2010). This defines whether the zone is moist (A), dry (B) or marine (C). No climate change model data is provided for climate zone 8, therefore climate zone 8 is not included in this analysis. All cities in the lower 48 states are classified in climate zones 1–7 so the study still encompasses a very large area. The analysis also only considers dbt that only affects HDD or CDD. Subtypes are thus ignored. A list of the ASHRAE climate zones chosen and the representative city can be seen in Table 3 (ANSI/ASHRAE/IES 2010). Using 7 climate zones will ensure that no matter the location, the reference models will still provide the wide range of climate change effects. Once the 4 reference models are identified, a validation of each model is performed, in which each model is used to predict TMY3 data (1991–2005) using TMY2 data (1961–1990) to prove the accuracy of the models and the morphing process.

Table 3 Representative cities and corresponding climate zone

Representative city	Climate zone
Miami, Florida	1
Phoenix, Arizona	2
Las Vegas, Nevada	3
Albuquerque, New Mexico	4
Boulder, Colorado	5
Helena, Montana	6
Duluth, Minnesota	7

4.4 Data analysis and discussion

(1) Projected climate data

Previous studies that estimate the effects of climate change have only used a small number of model scenarios. This could produce a smaller range of climate change possibilities. This study uses a larger number of model scenarios in order to explore if outputs from different models within the same scenario may differ. To show the variation, a statistical analysis of 56 model scenarios was conducted. The 56 model scenarios were first grouped into their respective RCP groups. For each group, an average, standard deviation and range of CDD was calculated. CDDs relate a temperature profile to energy demand, therefore this unit was used in estimating the effects of changing temperature due to climate change on building energy demand without using energy modeling software. Balance point temperatures of 10 °C and 18 °C were used for calculating CDD and HDD, respectively. This analysis took into considerations all 7 climate zones and 3 time periods. A similar trend was found for all 7 climate zones. Results for Boulder, Colorado are presented here to illustrate the findings. Results for all climate zones can be found in the Appendix in the Electronic Supplementary Material (ESM) of the online version of this paper.

The distribution of calculated CDD for all 56 model scenarios differs with time period. As time goes by, the RCPs create a wider distribution of possible climate change outcomes. Three histograms in Figs. 2–4 show how the distribution of models expands over time. The distribution of Period 1 resembles a normal distribution. It is a much tighter distribution. The distribution in Periods 2 and 3 begins to widen. Different RCP scenarios result in larger or smaller CDD so this is expected.

It is important to analyze the distribution within each RCP scenario. This can help find the range of differences between models when the RCP is consistent. An average CDD for each RCP scenario at each time period was calculated as shown in Table 4. For reference, the CDD from the existing TMY data was calculated to be 1649.1958. The trend in CDD is developed as expected. As the RCP and time period increase, the CDD value increases. The standard deviation and range values of projected CDD are presented in Tables 5 and 6. Both the standard deviation and range values increase with time. Period 3 from 2070 to 2099 shows much higher values for all RCP scenarios. There is not a clear trend when comparing different RCP scenarios within the same time period.

The range of the data is the most telling variable. It is observed that the maximum range for the RCP scenarios is from 272 to 873 (Table 6). That range indicates that different models within the same RCP scenario yield largely different results for building cooling energy use. For instance, based on the CDD calculated for the RCP8.5 scenario there was a range of 873 (out of the average value of 2757) for Period 3 (Table 4). Using the weather files generated from the minimum and maximum model that created this range, the building simulation model will surely predict a large difference in building energy demand.

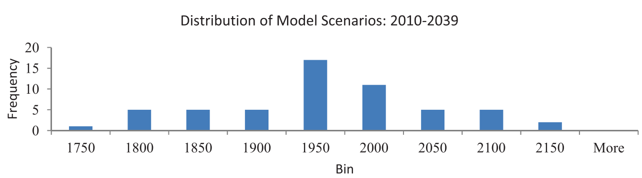

Fig. 2 Histogram representing 56 models corresponding CDD: 2010–2039

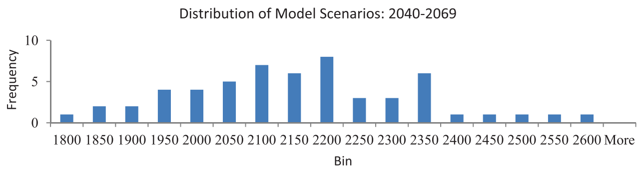

Fig. 3 Histogram representing 56 models corresponding CDD: 2040–2069

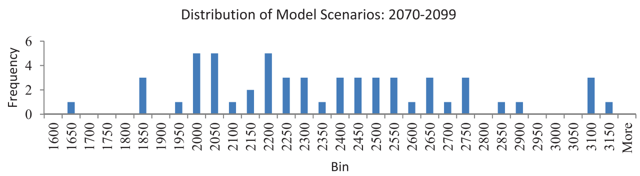

Fig. 4 Histogram representing 56 models corresponding CDD: 2070–2099

Table 4 Calculated average CDD for Boulder, CO

RCP scenario	2.6	4.5	6	8.5	TMY
Period 1	1946.911	1912.166	1921.55	1951.811	1649.196
Period 2	1998.778	2131.657	2109.454	2293.554	1649.196
Period 3	1973.885	2235.334	2386.9	2757.174	1649.196

Table 5 CDD standard deviation for Boulder, CO

RCP scenario	2.6	4.5	6	8.5
Period 1	97.2534	104.9028	89.52215	82.0257
Period 2	121.968	166.2464	123.0655	173.6928
Period 3	153.5686	211.1059	206.4178	269.7973

Table 6 CDD range for Boulder, CO

RCP scenario	2.6	4.5	6	8.5
Period 1	372.5764	353.0451	329.7498	272.1891
Period 2	414.3299	515.9633	485.8054	599.9505
Period 3	584.6505	717.0633	778.1585	873.618

(2) Identification of reference models

For application convenience, four reference models are to be identified that can fully encompass the range of all 56 model scenarios. These four identified reference models act like the 12.5%, 87.5% and median models, with the high one covering the top 12.5% of the range, the low one covering the bottom 12.5%, while the other two covering the median 75% of the predicted range (as illustrated in Fig. 5). To ensure that the reference models will hold true for all cities and time periods, 21 hourly profile scenarios are used representing 3 time periods and 7 climate zones. For each of the 21 scenarios, the CDD for each of the 56 models are sorted from low to high. Sorted distribution for each model scenario is created and the 4 reference model scenarios are then identified. The 4 model scenarios selected represent

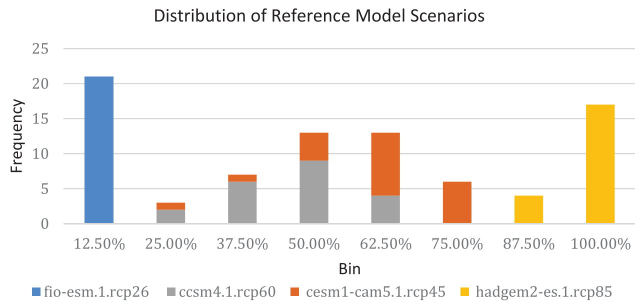

Fig. 5 Histogram distribution of representative models

a low, low-mid, mid-high, and a high scenario. Each RCP scenario is also represented. The final chosen models and scenarios are:

- Lower Bound Model and Scenario: fio-esm.1.rcp26 by The First Institute of Oceanography, SOA, China;
- Middle Bound Model and Scenarios: cesm4.1rcp45 and ccsm4.1.rcp60 by National Center for Atmospheric Research, USA;
- Upper Bound Model and Scenario: hadgem2-es.1.rcp85 by Met Office Hadley Centre, UK.

A histogram shown in Fig. 5 displays the chosen model scenarios and their sorted distributions when compared to the 56 other model scenarios. The bin percentage is used to graphically represent the distribution. For example, the 12.5% bin means that when the model scenario is sorted by low-high value, it is located at the bottom 12.5% of the 56 models. Each model scenario has 21 hourly profiles so each model has a total frequency of 21. Figure 5 shows that the fio-esm.1rp2.6 model scenario best represents the lower bound by falling in the bottom 12.5% for all 21 scenarios. The two middle models fall within the 25%–75% bin, accurately representing the middle bounds with the model scenarios. The high model scenario chosen, hadgem2-es.1rcp8.5, is the best fit for the upper bounds of all 56 model scenarios. These 4 models can thus precisely represent the wide range of all 56 models.

(3) Validation of climate projections with reference models

In order to validate the accuracy of the 4 reference models and the morphing process, TMY3 data was predicted using the climate model data and TMY2 data. This can ensure that the data source and morphing process produce an accurate prediction for climate variables as desired. The TMY2 data is for Boulder, Colorado. Three variables were validated for accuracy: average monthly dry bulb temperature, monthly maximum temperature, and monthly minimum temperature. All three variables are used in the Morphing Algorithm for dry bulb temperature calculation so their accuracy is critical. A comparison of actual TMY3 data and projected TMY3 data is presented in Figs. 6–8.

Figure 6 shows a comparison of average monthly dbt. The results show that the accuracy of the predicted TMY3 monthly dbt is within 10% of the actual values. The same outcomes are found for maximum and minimum temperature. Although the majority of data points lie within the 10% error, some points spread outside. Many of the points lying outside the 10% error occur when the dbt, maximum and minimum temperature are between −5°C and 5°C. Since the actual data value is small, a small deviation will produce a large percent error. Overall, the climate model

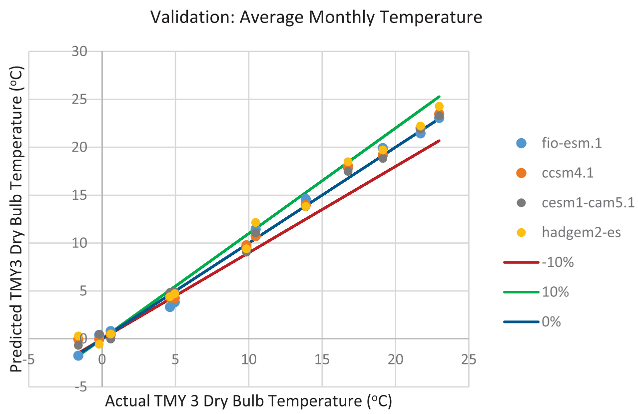

Fig. 6 Average monthly temperature validation

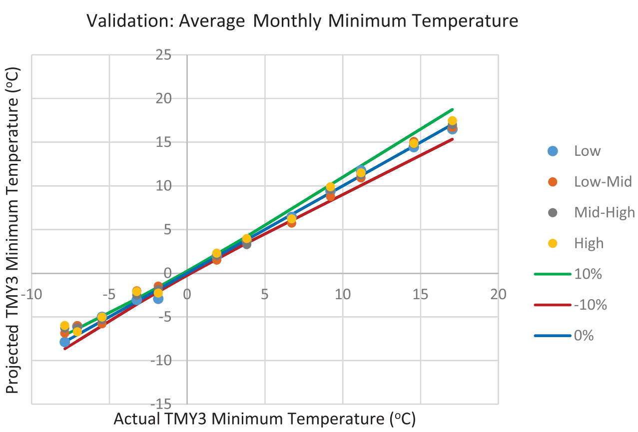

Fig. 7 Average minimum temperature validation

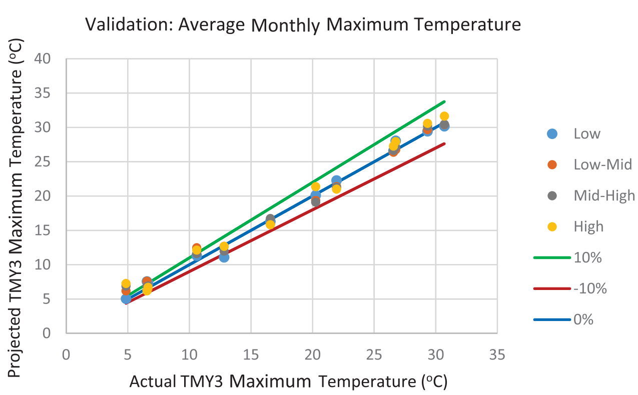

Fig. 8 Average maximum temperature validation

data and the Morphing Algorithm provide an accurate prediction of climate variables.

5 Implications of climate change to building energy use

5.1 Implications to different reference buildings

The implications of climate change to building energy use is tested on typical single buildings. The future weather files generated for Ann Arbor, MI, are applied to five US DOE reference buildings including secondary school, outpatient care, large office, small office, and apartment. These reference buildings represent a wide range of building function in the US. The reason of choosing Ann Arbor, MI, as an example is that energy monitoring data is available to calibrate the base energy models for the five reference buildings.

The building energy simulations reveal a similar general trend for all the tested buildings: the site energy decreases and the source energy increases. The site to source conversion factor used for natural gas is 1.092 and 3.546 for electricity. Figures 9 and 10 show the results for the outpatient care building. The pattern holds true for the majority of the tested climate models and buildings.

The decrease in site energy is because of the decrease in heating energy while the increase in source energy is because of the increase in cooling energy. When taken from the source, electricity has a much higher conversion factor; hence, the increase in electricity dominates. Figure 11 shows the cooling and heating site energy changes for DOE office buildings in climate zone 5A (Ann Arbor) by 2080. Similar trends were found in literature. Wang and Chen (2014) projected that for 9 commercial buildings (based on DOE reference buildings) in climate zone 5A (Chicago) the site energy generally decreases and the source energy increase. A comparison of two investigation results is presented in Table 7. According to Table 7, the changes in site cooling and heating energy show very similar trends, with a wider

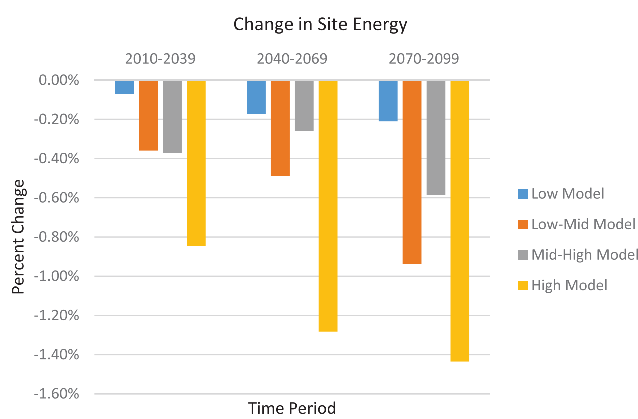

Fig. 9 Change in site energy (%) for outpatient care building in Ann Arbor, MI

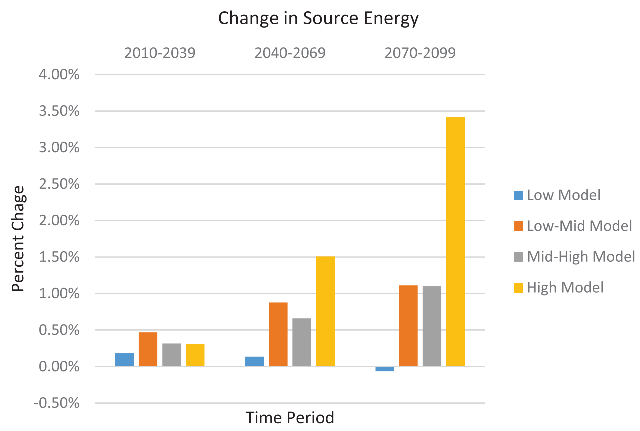

Fig. 10 Change in source energy (%) for outpatient care building in Ann Arbor, MI

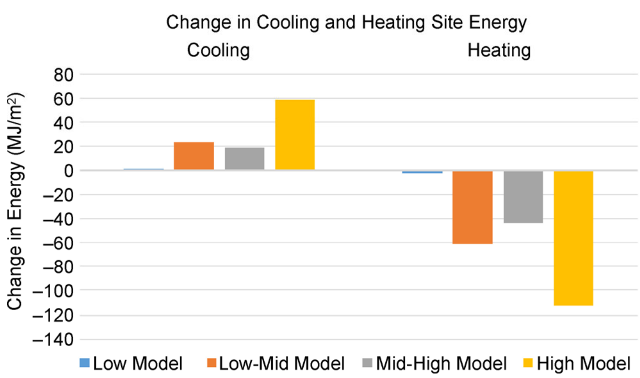

Fig. 11 Changes in cooling and heating site energy for office buildings in Ann Arbor, MI

Table 7 DOE case study results compared with literature

DOE case study comparison	Wang and Chen (2014)	This study
Change in site cooling energy (MJ/m^2)	20 to 45	0 to 60
Change in site heating energy (MJ/m^2)	−60 to −100	−2 to −110
Change in total source energy (MJ/m^2)	−5 to 40	−7 to 114

range in this study. This is probably due to the wider range of climate scenarios used in this study (especially RCP2.6). This wider range causes larger differences in total source energy.

5.2 Influences of humidity

This study ignored the potential changes in humidity. Humidity was assumed unchanged. In order to examine how humidity may affect the predictions, a sensitivity analysis was performed. The sensitivity analysis encompasses 3 climate zones and 2 subtypes to explore how the changes in humidity may affect heating dominated climates, cooling dominated climates, humid climates, and dry climates. The four locations chosen with corresponding climate zones are listed in Table 8. The letters following the climate zones number represents the climate zone subtype. "A" represents a moist climate, and "B" represents a dry climate. There are no subtypes for climate zones 7 and 8. Furthermore, 3 building types were analyzed using DOE benchmark models. Using the base TMY weather files for each location, the hourly relative humidity values were altered by −25%, −10%, 10% and 25%. These four scenarios allow to investigate how a wide range of humidity changes will affect building energy use for multiple climate zones and building types.

Adjusting the hourly RH profiles by the four scenario percentages does not always result in an equal increase or decrease in average annual RH. Because the RH is limited to 100%, an increase of an hourly term close to 100% shows a smaller percentage increase than the original increase. Table 9 calculates the average annual RH (%) for each scenario and each location. It is important to note that a 25% change in either direction is an extreme scenario. It is included to demonstrate extreme cases of potential climate change. Once the RH profiles were adjusted, new weather files were created and were used in simulating the three DOE buildings. Tables 10–12 present the predicted changes in energy use intensity (EUI) for all locations and building types.

The results reveal a few very important points. First, the EUI in Miami is much more affected by changes in RH than any other location. This is because Miami is the only cooling dominated climate used. Changes in RH have a

Table 8 Humidity sensitivity analysis locations

Climate zone	Representative city
1A	Miami, Florida
5A	Ann Arbor, Michigan
5B	Boulder, Colorado
7	Duluth, Minnesota

Table 9 Average annual RH (%)

	−25%	−10%	Base (0%)	10%	25%
Miami	54.5	65.3	72.6	79.6	87.6
Ann Arbor	55.9	67.1	74.6	79.9	85.5
Boulder	38.5	46.2	51.3	56.3	63.0
Duluth	53.7	64.4	71.6	77.7	84.5

Table 10 School building change in EUI (%)

School building	−25%	−10%	10%	25%
Miami	−5.28%	−2.00%	2.32%	4.65%
Ann Arbor	−0.77%	−0.33%	0.33%	0.78%
Boulder	−0.21%	−0.11%	0.13%	0.35%
Duluth	−0.27%	−0.12%	0.13%	0.32%

Table 11 Office building change in EUI (%)

Office building	−25%	−10%	10%	25%
Miami	−5.14%	−1.69%	2.52%	4.69%
Ann Arbor	−1.45%	−0.59%	0.50%	1.14%
Boulder	−0.42%	−0.18%	0.22%	0.62%
Duluth	−0.67%	−0.32%	0.35%	0.77%

Table 12 Apartment building change in EUI (%)

Apartment building	−25%	−10%	10%	25%
Miami	−4.38%	−1.41%	2.28%	4.12%
Ann Arbor	−0.32%	−0.13%	0.14%	0.32%
Boulder	−0.24%	−0.10%	0.10%	0.26%
Duluth	−0.09%	−0.04%	0.04%	0.11%

much larger effect on the cooling systems when compared with the heating systems. Therefore, if a climate is cooling dominated it will be more sensitive to change in RH. The other 3 locations show that changes in RH have very little effect on EUI. When comparing Ann Arbor to Boulder, it is found that Ann Arbor is more sensitive. This is because average annual RH in Ann Arbor is higher than in Boulder so the absolute changes in Ann Arbor were greater. Finally, the sensitivity varies with the three building types. The apartment building is the least sensitive because it has the lowest cooling load. The office and school buildings have higher cooling loads and thus are more sensitive to the changing relative humidity.

Overall, it can be concluded that changes in RH will affect locations and buildings with higher cooling loads more. Heating dominated climates show very little sensitivity to changing RH. Although larger changes in EUI are found for cooling dominated climates, the changes are relatively small when compared to the effect of dry bulb temperature. Overall, dry bulb temperature still dominates the changes in building energy consumption, and relative humidity only has a relatively larger impact on extreme cases in cooling dominated climates.

6 Conclusions

When applying climate models to project future climate change scenarios and impacts on buildings, a limited number of models were often used in practice due to the complication of the models and availability of the data. Analysis of 56 model scenarios approved from the IPCC revealed that the range of model projections varies significantly. Within each RCP scenario, results from a simple degree day analysis indicate that this range can have a large impact on the predicted energy consumption of individual buildings. The 56 climate model scenarios tested in this study were chosen based on two factors: relative error in TAS, and data availability. Once the 56 models were selected, 4 representative models were identified for application convenience. The four models selected were: FIO-ESM v1.0 (Low), CESM1-CAM5 (Middle), CCSM4 (Middle), and HadGEM2-ES (High). Together, these models can accurately represent the distribution of all 56 models, while simplifying the application. Using a morphing algorithm, these representative models were validated for accuracy. TMY3 data projected from these models was compared to the actual TMY3 data. In general, the models accurately predicted the change in average monthly temperature, average maximum temperature, and average minimum temperature to within 10%. Using climate change model data and TMY data, hourly future weather files under particular climate scenarios can be created for detailed building energy simulation and analysis.

As a demonstration, energy use of 4 reference building types in a heating dominated climate (Ann Arbor, Michigan) was projected using the generated future weather files from the 4 representative models. The building energy simulations reveal similar general trends for all the tested buildings: (1) the heating energy decreases and the cooling energy increases; (2) the site energy decreases and the source energy increases. The decrease in site energy is because the more decrease in heating energy than the increase in cooling energy for this heating dominated location. The increase in source energy is because of the increase in cooling energy and the much higher site-to-source conversion factor for electricity. The situation is anticipated to become worse for cooling dominated locations such as Miami, Florida. The sensitivity analysis on the influences of relative humidity changes in future climates indicated that relative humidity has a relatively larger impact on extreme cases (more than 25% variation in RH) in cooling dominated climates and dry bulb temperature still dominates the changes in building energy consumption. When more warm climate zones migrate to the hot climate due to the climate change eventually, a comprehensive study projecting both air temperature and humidity changes and influences will become desirable.

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