Climate Change and Its Impact on Building Energy Consumption in Office Building of Different Climate Zones in China

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Abstract

In this study, ten cities from different climate zones in China were selected to analyse the impact of climate change on building energy consumption in offices. We obtained real historical climatic data of 1960-2014 (1960-2013 for Xi'an) and future climate prediction from the simulation results of the regional climate model (RCM) under two representative concentration pathways (RCPs) (i.e., the high-level RCP8.5 and mid-level RCP4.5). Climate changes rapidly, and its variation may not be the same during different periods, which also leads to disparate heating/cooling loads in buildings. In this study, we found that the variation of building loads ranges from 40% to 400% in different cities under climate change. We should draw more attentions about climate change and its likely impact on building energy, guiding the future building and HVAC system design.

Introduction

Buildings act as the interface between the outdoor environment and the indoor environment to protect the safety and comfort of the indoor occupants from the outdoor. Therefore, the outdoor environment, subjected to the climate change, has a significant influence on building performance. As global warming is an unquestioned fact (IPCC 2013), carrying out the study of the impact of climate change on building performance has practical importance to heating, ventilation and air conditioning (HVAC) system design, building energy efficiency evaluation, and the operating strategies of building automatic control system, etc.

With the growing concern about implications of climate change, many researchers present their work of the impact analysis of climate change in various building types in different countries (De Wilde, P., and Coley, D (2012)). Some researchers focus on providing more suitable weather data for future building energy estimation and HVAC system sizing (Nik, V. M. (2016), Kershaw, T.(2011), Chinazzo, G.(2015)), some researchers contribute to analyzing the impact degree of climate change on building energy (Patidar, S.(2014)), while others study the retrofitting effect of buildings in face of climate change (Chow, D. H.(2013)).

China is the second largest economy in the world with multiple climates. Significant warming in the last decades has also occurred in China at a larger rate than the global mean value according to the research results of CCSNARCC (2011), Zhai PM and Pan X (2003). Climate change also has a big influence on building energy conservation work in China. To achieve the building energy savings targets defined in the strategic 13th Five-Year Plan, we should also consider climate change factors when deciding the policy, standard and guidance. Although some researches (Wan.K.K et al. (2011)) have contributed to this area, knowledge concerning impact of building energy usage to climate change is still limited for China, and has some deficiencies. At first, we should consider more cities, which are located in various climate zones. In addition, different climate prediction models should be taken into considerations to improve the accuracy of analysis. Thus, we carried out the impact analysis work of climate change in China to investigate the future trends of building energy consumption in office buildings in different climate zones.

Methodology

Overview

In order to analyse the impact of climate change on building energy consumption in offices across China, we need to estimate the building loads for decades from the past time to the future based on weather data. Taking dynamic building energy simulation tools (e.g., Energy plus, DOE-2, DeST(Yan D., et al.(2008)) is a popular and professional method to perform hourly computation of heating/cooling loads with hourly weather files (Jenkins, D. P., et al. (2011)). However, hourly weather data are not easy to access, thus regression-based model based on daily, weekly or monthly climatic variables is another good choice to deal with this issue.

Therefore, we used dynamic building energy simulation tool to calculate the building loads in the past time, and regression model to carry out our study of prediction of future building loads trend with the following steps:

1) Weather data collection: we selected 10 cities as research objects, and obtained the historical and future weather data;
2) Multi-year building loads simulation: simulating building heating/cooling loads of a prototype office building in various cities based on real historical weather data with simulation tool DeST.
3) PCA of major meteorological variables: we carried out PCA (Storch HV and Zwiers FW (1999)) of historical weather data and future weather predictions to generate some new climatic

parameters, which could reflect the main features of original climatic variables to building loads.

4) Regression analysis: analysing the correlation between simulated heating/cooling loads with corresponding climatic principal components in the past.
5) Regression model evaluation: evaluating the regression model by comparing simulation results and regression-predicted results.
6) Future trend of building loads: using the evaluated regression model to estimate future building loads under two RCPs (the high-level RCP8.5 and mid-level RCP4.5). Finally, analysing the change of building loads under climate change from the past time to the future.

Weather data collection

China is a large country with various climatic conditions. It has five climate types, namely the severe cold zone (SCZ), the cold zone (CZ), the hot summer and cold winter zone (HSCWZ), the hot summer and warm winter zone (HSWWZ), and the temperate zone (TZ). In this study, we selected one or multiple cities within each of the five major climate zones, and finally we investigated ten cities cross China. Detailed information for each site is listed in Table 1.

Table 1: Summary of information for 10 cities in China

No.	City	Climate zone	Latitude	Longitude
1	Harbin	SCZ	45°56’	126°34’
2	Urumqi	SCZ	43°47’	87°39’
3	Beijing	CZ	39°48’	116°28’
4	Lhasa	CZ	29°40’	91°08’
5	Xi’an	CZ	34°18’	108°56’
6	Shanghai	HSCWZ	31°24’	121°27’
7	Hangzhou	HSCWZ	30°14’	120°10’
8	Guangzhou	HSWWZ	23°13’	113°29’
9	Haikou	HSWWZ	20°00’	110°15’
10	Kunming	TZ	25°00’	102°39’

We obtained the historical weather data from 1960 to 2014 within the 10 cities from the China National Meteorological Centre, which were collected from the meteorological stations, including the dry-bulb temperature (DBT), relative humidity, wind speed and direction, ground temperature, atmosphere pressure (AP) and solar radiation (SR). The Xi’an station, however, only had a 54-year record, and its meteorological record ended in 2013.

RCM and general circulation model (GCM) are two common methods to predict future weather. In this study, daily future weather data were from the simulation results of the RCM under two RCPs (i.e., the high-level RCP8.5 and mid-level RCP4.5), which were conducted with Abdus Salam International Climate Centre for Theoretical Physics (ICTP) Regional Climate Model v.4, RegCM4 (Giorgi F, et al. (2012)), and driven by the global model BCC_CS1.1. The RegCM4 domain covers continental China and surrounding areas from 1951 to 2099. Gao et al. (2013) demonstrated that RegCM4 has remarkable improvements in reproducing the present day climate over the region compared to the driving GCM. It is worthy to mention that we only used the period 2015-2050 for predicting the future building load, and the period 1980-2005 was used to estimate the regression model. These data include mean DBT, maximum DBT, minimum DBT, mean moisture content (MC), mean SR and mean AP.

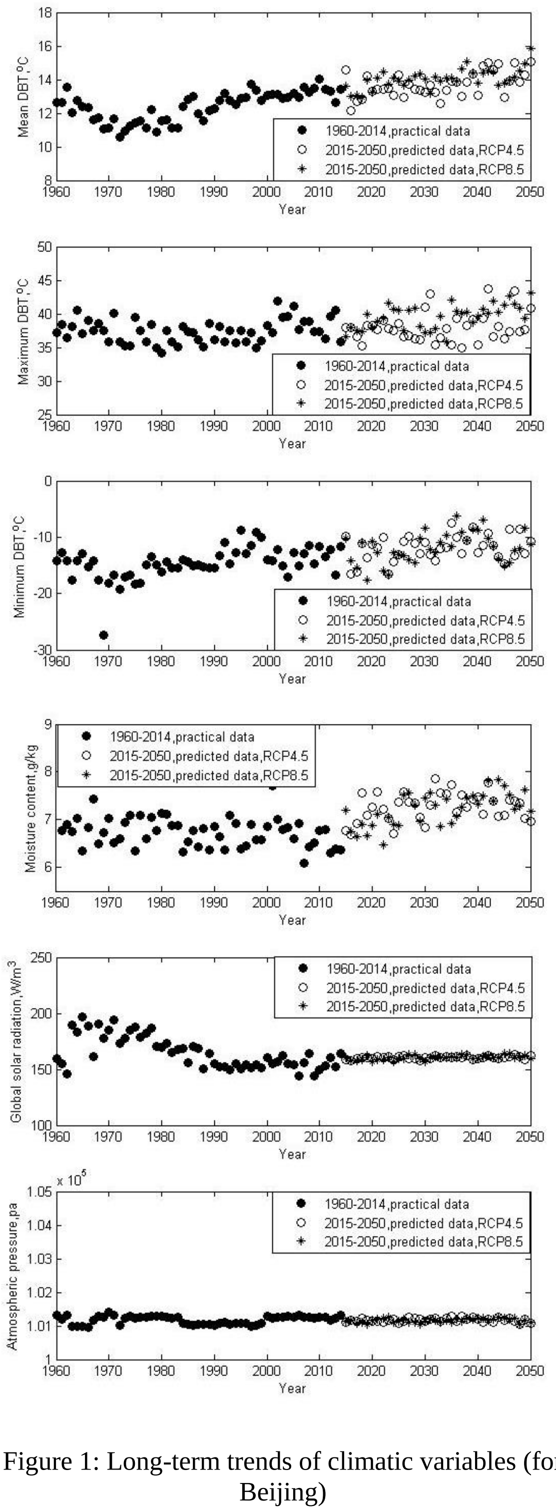


Figure 1: Long-term trends of climatic variables (for Beijing)

After analysing the climate trends from 1960 to 2050, we can conclude that there is remarkable climate change of

DBT, and the change scope varies among different cities. However, other climatic variables such as global solar radiation are not significant.

Taking Beijing as an example, as curves shown in Figure 1, the coldest year occurred in 1971, and the mean DBT increase 2.9 ^oC and 4.2 ^oC separately under RCP4.5 and RCP8.5 from 1971 to 2050. The maximum DBT and minimum DBT also increase significantly. However, there's no obvious change on the moisture content, solar radiation and atmosphere pressure.

Multi-year building loads simulation

Hourly energy simulations were conducted for each city of the 55 years (54 years for Xi'an) with the simulation tool DeST. We used a real medium-size office building with seven stories and a total floor area of 5550 m^2 as the prototype model, as shown in Figure 2. The shape coefficient of the building was 0.176 and the window-wall ratio was 0.4 for all four orientations.

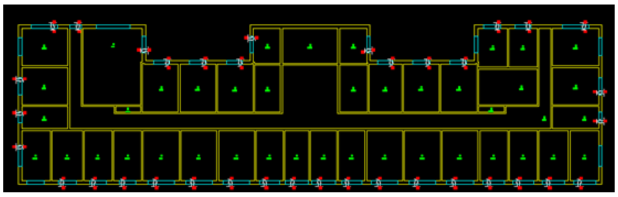


Figure 2: Floor plan of prototype model

The occupant density was 10 m^2/person and the lighting and equipment densities were 9 W/m^2 and 15 W/m^2, respectively. The working hours were 07:00–18:00 from Monday to Friday. We configured the building envelope properties according to the Chinese national standard for public buildings (Bureau B C (2005)), and some detailed values are shown in Table 2. We also developed the HVAC system based on the design code mentioned above. In brief, the operating hours of the HVAC system were the same as the working hours. The set point temperature was 26 ℃ in summer and 20 ℃ in winter.

Table 2: Building envelope characteristics in the 10 cities in China

No.	City	U-values (W/m^3/k)			Window SHGC
		Roof	Wall	Window	
1	Harbin	0.28	0.38	2.2	N/A
2	Urumqi	0.35	0.43	2.3	N/A
3	Beijing	0.45	0.5	2.4	0.48
4	Lhasa	0.45	0.5	2.4	0.48
5	Xi'an	0.45	0.5	2.4	0.48
6	Shanghai	0.5	0.8	2.6	0.44
7	Hangzhou	0.5	0.8	2.6	0.44
8	Guangzhou	0.8	1.5	3	0.35
9	Haikou	0.8	1.5	3	0.35
10	Kunming	0.8	1.5	3	0.4

Taking Beijing as an example to show its building load change with climate. Figure 3 illustrates that cooling load was twice or three times of heating load in 1960-1964 because the warm weather. However, the temperature decreased sharply until around 1980, therefore, cooling load decreased and heating load increased during that period. From 1980 to now, the cooling load increased and heating load decreased with the climate getting warmer and warmer. In general, climate changed significantly from 1960 to 2014, but the changing trend was not always consistent. Climate changes has a conspicuous influence on building loads. Biggest cooling load variation is around 65.6%, while the biggest heating load variation is around 45.3% in Beijing from 1960 to 2014.

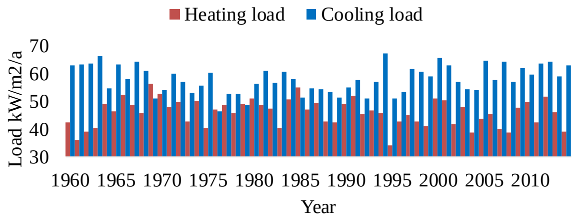


Figure 3: Building load variation with climate change from 1960 to 2014

PCA of major meteorological variables

We consider six climatic variables in the model, namely mean DBT, maximum DBT, minimum DBT, mean MC, mean SR and mean AP. DBT and DR can affect the heat gain/loss through the building envelope, therefore, they have strong influences on sensible cooling/heating load. MC can influence the humidity load, which need to be added or removed by air-conditioning system too. In addition, the material properties of envelope change with different AP, then affecting the building load. Through correction analysis of simulated building loads and these six climatic variables from 1960 to 2014, we conclude that all these variables have significant influences on building loads. So these variables should be considered to carry out prediction of building energy use.

However, as these variables are inter-correlated, PCA is a good method to categorise the group meteorological variables as one or more cohesive indexes, which also provides a better understanding of the cause relationship. In addition, PCA is one of the most popular statistical method with the characteristics of simple and easy to use. Therefore, we choose PCA method in this study.

After being calibrated according to the mean bias error between real weather data and predicted weather data during 1980-2005, 36-year predictions (37 years for Xi'an) under two RCPs (i.e., the high-level RCP8.5 and mid-level RCP4.5) together with 55-year (54 years for Xi'an) measured data were used to calculate the PCA.

The predicted future climatic data from RegCM4 were recorded every day, but one-day interval are too short to perform PCA considering the thermal inertia of building envelope. Therefore, we generated weekly data and monthly data to obtain corresponding principal components in this study.

We kept the principal components whose corresponding eigenvalues were greater than one, because the new component contains more information than any original climatic variables if its corresponding eigenvalue larger than one. We take Beijing as the example again. For Beijing, we only kept one principal component, which stands for around 85% of original information. Table 3 shows the coefficients of the first principal components and the relevant statistics from the PCA for Beijing.

Table 3: Summary of principal component analysis (for Beijing)

Time interval	Scenario	Eigenvalue of 1st principal component	Cumulative explained variance	Coefficient					
				Mean DBT	Maximum DBT	Minimum DBT	Mean MC	Mean SR	Mean AP
A week	RCP4.5 (mid-level)	5.097	84.944%	0.193	0.190	0.189	0.176	0.160	-0.174
	RCP8.5 (high-level)	5.095	84.917%	0.194	0.190	0.189	0.176	0.160	-0.174
A month	RCP4.5 (mid-level)	5.327	88.778%	0.185	0.181	0.183	0.172	0.164	-0.174
	RCP8.5 (high-level)	5.317	88.612%	0.186	0.181	0.182	0.173	0.165	-0.175

The first principal component could be determined as a linear combination of the standardized original six climatic variables as follows:

$$Z = A \times \text{Mean DBT} + B \times \text{Maximum DBT} + C \times \text{Minimum DBT} + D \times \text{MeanMC} + E \times \text{MeanSR} + F \times \text{MeanAP} \quad (1)$$

Figure 4 and Figure 5 show the weekly and monthly values of Z for the past and future period under mid-level RCP4.5. Z has significant seasonal variations. The average values of Z during the past time are lower than Z values during 2015-2050.

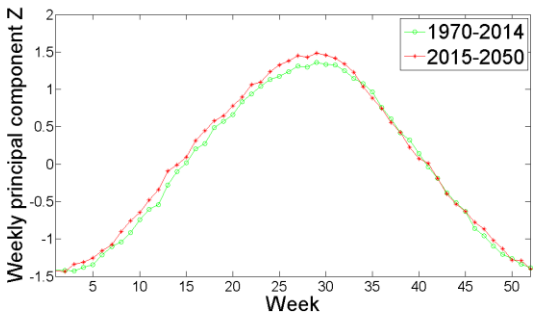


Figure 4: Weekly profiles of principal component Z during 1960-2050 (for Beijing, RCP4.5)

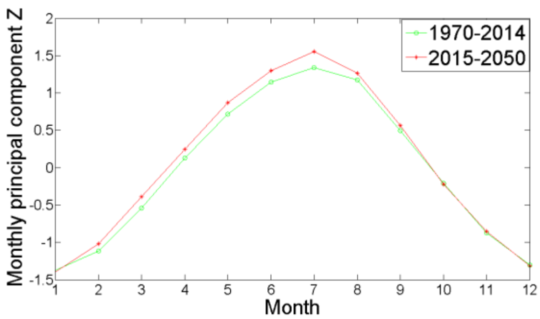


Figure 5: Monthly profiles of principal component Z during 1960-2050 (for Beijing, RCP4.5)

In addition, Figure 6 reflects an upward trend in the principal component Z in Beijing from 1970 to 2050, which consistently matches the conclusion drew from original climatic parameters.

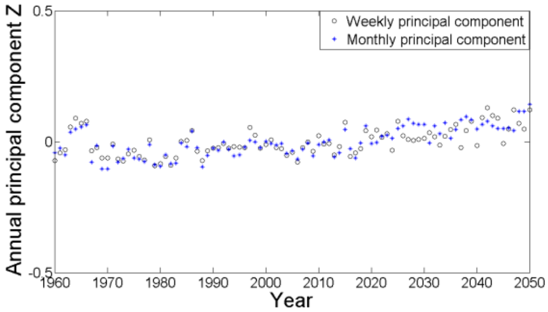


Figure 6: Long-term trend of annual average principal component Z during 1960-2050 (for Beijing, RCP4.5)

We also carried out similar analysis for the other nine cities. It is noted that all cities kept the first principal component except Kunming, and Kunming has two principal components whose corresponding eigenvalues are bigger than one.

Regression analysis

We conducted regression analysis for both weekly and monthly building loads and the corresponding principal component from 1960 to 2009 by using a quadratic regression ($Y=a+bZ+cZ^2$, which Y stands for building heating/cooling load), to obtain the regression coefficient between building load and principal component. The summary of regression analysis of weekly or monthly heating/cooling load in Beijing are shown in table 4.

Table 4: Summary of regression analysis results for Beijing

Time interval	Load	Scenario	a	b	c
A week	Heating	RCP4.5	242	-963	600
		RCP8.5	234	-959	608
	Cooling	RCP4.5	-535	-1230	-604
		RCP8.5	-547	-1248	-611
A month	Heating	RCP4.5	665	-4275	3057
		Cooling	672	-4332	3123
	Cooling	Heating	-2043	-5438	-2998
		Cooling	-2035	-5482	-3060

We displayed the R^2 of regression model in ten cities in Figure 7 and Figure 8. We can conclude that the R^2 of regression model in most cities is usable to carry out future predictions on the building load. In addition, monthly regression model fits original data better than weekly model due to less original data. However, regression models in Kunming and in Lhasa for cooling load are not satisfactory, and the possible reason might be the original six climatic parameters do not include the most important influencing factors for predicting the cooling load in Kunming and Lhasa.

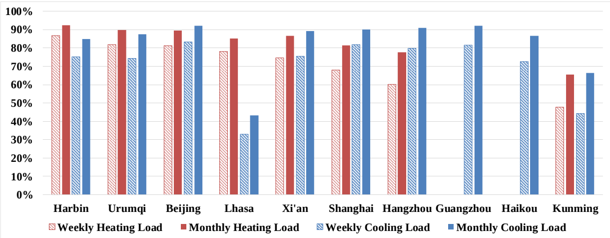


Figure 7: Summary of the R^2 of regression analysis under RCP4.5

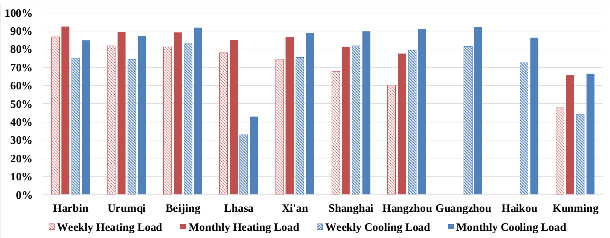
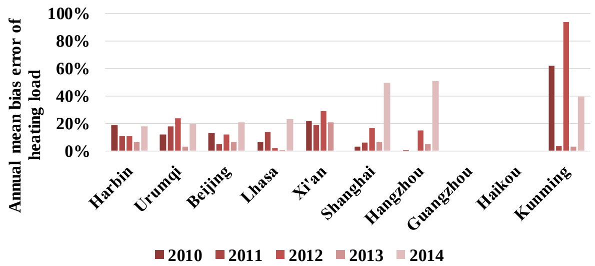


Figure 8: Summary of the R^2 of regression analysis under RCP8.5

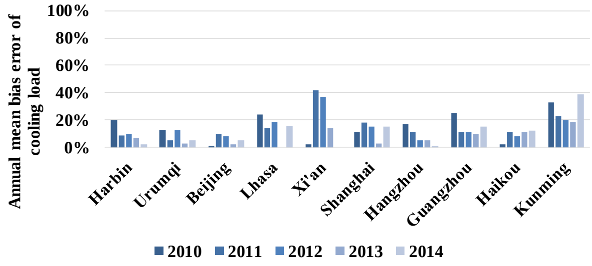
Regression model evaluation

We evaluated the regression models by comparing the simulated and the predicted results from the regression models during 2010 to 2014 (2010-2013 for Xi'an), and the comparison results are shown in Figures 9 and 10.

Most annual bias errors are less than 20%, which demonstrates that these regression models can be used to estimate future building loads in different cities. However, annual bias errors of heating loads in Hangzhou and Shanghai, cooling loads in Lhasa, and heating and cooling loads in Kunming are large, so that we could not apply the previous regression models to these cities. However, as the known climatic parameters are limited, we have to use these regression models to carry out further analysis only to reflect the building load trend instead of specific values. Although monthly model fits better than weekly model in same situation, there is no significant differences in model evaluation results.

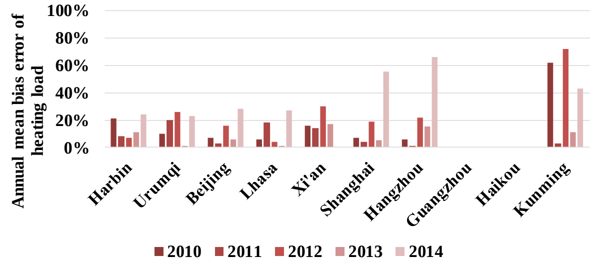


(a) Annual mean bias error of heating load

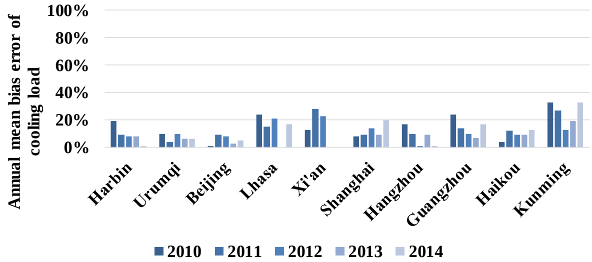


(b) Annual mean bias error of cooling load

Figure 9: Summary of weekly regression model evaluation (RCP4.5)



(a) Annual mean bias error of heating load



(b) Annual mean bias error of cooling load

Figure 10: Summary of monthly regression model evaluation (RCP4.5)

Future trends of building loads

We separately used weekly regression models and monthly regression models to estimate the heating and cooling loads in the future for the two scenarios (RCP4.5 and RCP8.5). Taking Beijing as the example again, as shown in Figure 11 and 12, we can conclude that the results using weekly regression model and monthly regression model are constituent with slight differences. Heating loads decreased slightly from 1970 to 2050, but the variation range of heating loads can be as large as around 33 -56 kWh/m^2/a under different RCPs and regression models. Oppositely, cooling load increased 25 kWh/m^2/a, which presents a significant upward trend.

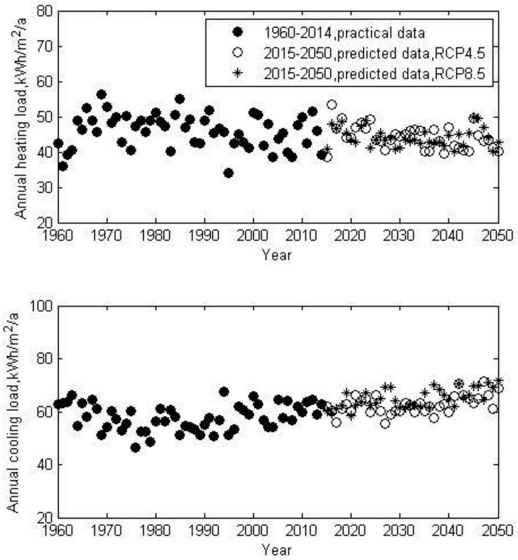


Figure 11: Long-term trends of annual building load (for Beijing, by using weekly regression model)

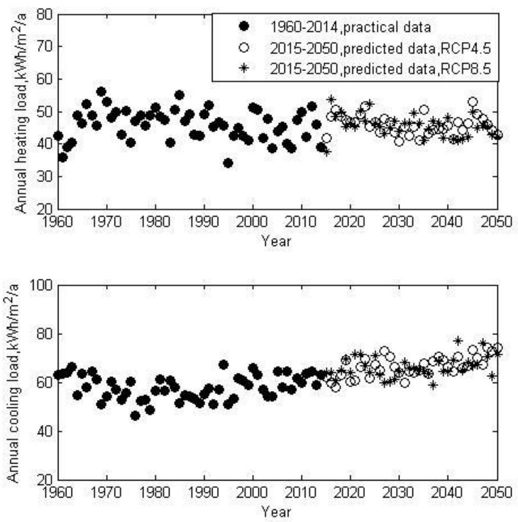


Figure 12: Long-term trends of annual building load (for Beijing, by using monthly regression model)

We summarized the variation range of annual heating/cooling loads in each city as shown in Figures 13-15. The variation range could be around 40% to 400%, which is big enough to draw more attentions about climate change and its impact on building energy. Climate change might have significant influence on building energy conservation policy in the future, such as the air-conditioning design standard and the promotion of energy saving techniques.

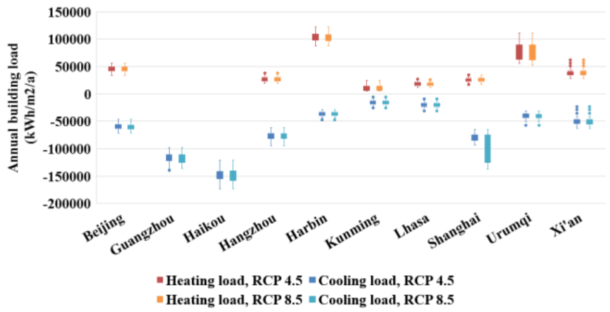


Figure 13: Statistics of annual average building load in 10 cities (by using weekly regression model)

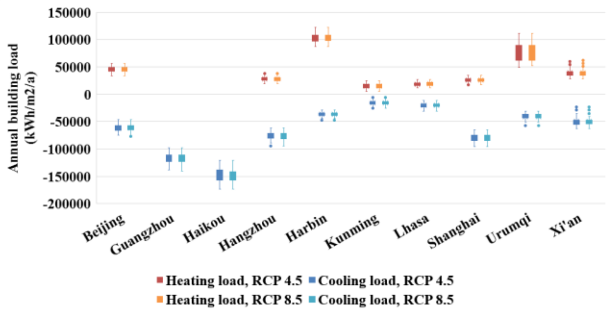
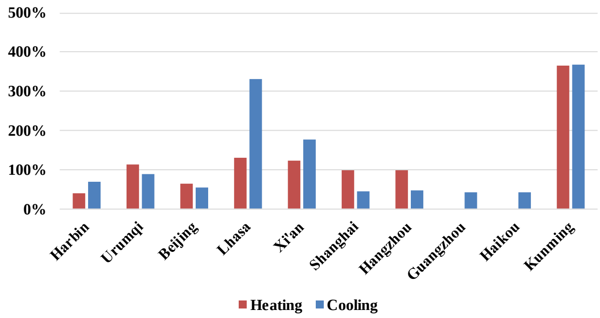
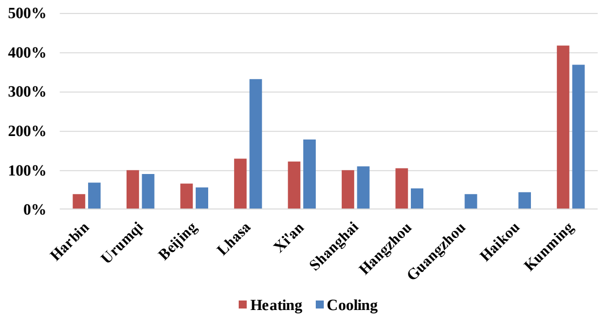


Figure 14: Statistics of annual average building load in 10 cities (by using monthly regression model)



(a) Results under RCP 4.5



(b) Results under RCP 8.5

Figure 15: The change rate of building loads in ten cities from 1960 to 2050 (by using weekly regression model)

Conclusions and limitations

In this study, we chose ten cities in China from different climate zones to analyse the impact of climate change on building energy consumption in offices. We obtained historical climatic data of 1960-2014 (Xi'an is 1960-2013) from the China National Meteorological Centre and future climate prediction from the simulation results of the RCM under two RCPs (the high-level RCP8.5 and mid-level RCP4.5). Then we conducted hourly energy simulations for each city of the 55 years (54 years for Xi'an) by using the simulation tool DeST with a prototype office building. Thirdly, PCA and regression analysis were carried out to acquire regression models of future building loads. Finally, combining hourly simulated building loads with estimated future loads, we analysed the variation range of building loads along with climate change. Main conclusions are presented as follows:

1) Climate change leads to significant variance of heating/cooling loads. The variation range could be around 40% to 400%, and cooling load increased 25 kWh/m^2/a from 1970 to 2050 in Beijing, which presents a significant upward trend. Therefore, we should pay more attentions about the impact of climate change on building energy.
2) We compared predicted building loads with weekly regression model and monthly regression model. Although monthly regression model fitted the original data better than weekly model (had larger R^2), there exist no significant differences in model evaluation results. Therefore, monthly regression model based on monthly weather data is sufficient to estimate building load when using PCA and regression analysis.
3) Due to the limitation of the collecting interval and types of future climatic data, the regression model sometimes could not estimate the building load very well, and annual bias errors of heating loads in Hangzhou and Shanghai, cooling loads in Lhasa, and heating/cooling loads in Kunming are too large. Therefore, we need to collect more kinds of climatic data with shorter time interval, and try more complex but accurate regression in the future to improve our work.

Abbreviations

RCM	Regional Climate Model
RCPs	Representative Concentration Pathways
HVAC	Heating, Ventilation and Air Conditioning
PCA	Principal Component Analysis
SCZ	Severe Cold Zone
CZ	Cold Zone
HSCWZ	Hot Summer Cold Winter Zone
HSWWZ	Hot Summer Warm Winter Zone
TZ	Temperate Zone
DBT	Dry-Bulb Temperature
AP	Atmosphere Pressure
SR	Solar Radiation
GCM	General Circulation Model
MC	Moisture Content
ICTP	International Climate Centre for Theoretical Physics
RegCM4	Regional Climate Model v.4

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