Applied Energy 261 (2020) 114295

Contents lists available at ScienceDirect

Applied Energy

journal homepage: www.elsevier.com/locate/apenergy

Climate-change impacts on electricity demands at a metropolitan scale: A case study of Guangzhou, China

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HIGHLIGHTS

- Cooling degree days is significantly related to electricity consumption.
- +1 °C in temperature will lead to +2.7% in total electricity consumption.
- +1 °C in temperature will lead to +0.9% in residential electricity consumption.
- Multi-ensemble of 13 climate models is used to estimate climatic conditions.
- Electricity consumption could vary significantly under different climate scenarios.

ARTICLE INFO

Keywords:
Global warming
Impact assessment
Decision support
Global Climate Models
Representation Concentration Pathways
Shared Socio-economic Pathways

ABSTRACT

This study was to quantify the effects of climate change on total electricity consumption (TEC) and residential electricity consumption (REC) at a regional scale, with a case study in Guangzhou, China. The Mann-Kendall test was used to explore the tendency of climate change. The best subset regression analysis was undertaken to develop electricity consumption models, as represented by a number of socioeconomic and climatic variables. The levels of electricity consumption and their variabilities (percentage changes) in 2016 to 2035 (the 2030s), 2046 to 2065 (the 2050s), and 2076 to 2095 (the 2080s) were then calculated under 20 scenario combinations, which were driven by five Shared Socio-economic Pathways (SSPs) and four Representation Concentration Pathways (RCPs). The results revealed that Guangzhou had a significant warming tendency till the end of the 21st century, with an increasing rate of 0.15 – 0.47 °C/decade (1986–2099) under four RCPs. With such a warming trend, the increased demand for cooling would lead to the raised electricity consumption. Furthermore, total electricity consumption would be more sensitive to climatic warming than residential electricity consumption. With a raised temperature of 1 °C, total electricity consumption would increase by 2.7%, and the residential one would increase by 0.9%. In addition, the projected impacts of climate change on electricity consumption would depend on the emissions of greenhouse gases. In other words, electricity consumption would vary significantly under four RCPs, with the impacts being increased gradually from RCP2.6 to RCP8.5. In the 2080s, total electricity consumption would be 161 TWh under RCP2.6, while the residential one would be 44 TWh. In comparison, under RCP8.5, total electricity consumption would be 171 TWh, while the residential one would be 45 TWh. Under global warming, total electricity consumption would increase by 3.2%–10.4% by 2080s, compared with the baseline period from 1986 to 2005; for residential electricity consumption, the relevant increases would be 1.1%–3.5%.

1. Introduction

The Fifth Assessment Report (AR5) of Intergovernmental Panel on Climate Change (IPCC) indicated that the global mean surface temperature has increased by 0.85 (with a range of 0.65–1.06) °C from 1880 to 2012, while the temperature would likely increase by 1.5 (with a range of 0.3–4.8) °C at the end of the 21st century [1,2]. It is evident that climate change could significantly affect electricity consumption since the changing temperature will alter heating and cooling loads [3]. Cold countries will have benefits due to the rise of temperature, as less energy will be required for heating during winter months. Meanwhile, more energy will be required for cooling during hot summers in tropical

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https://doi.org/10.1016/j.apenergy.2019.114295
Received 22 July 2019; Received in revised form 12 November 2019; Accepted 28 November 2019
Available online 21 December 2019
0306-2619/

Nomenclature

TEC	Total Electricity Consumption
REC	Residential Electricity Consumption
SSPs	Shared Socio-economic Pathways
RCPs	Representation Concentration Pathways
AR5	Fifth Assessment Report
IPCC	Intergovernmental Panel on Climate Change
GCMs	Global Climate Models
CMIP5	Coordinated Modelling Intercomparison Project Phase 5
GDP	Gross Domestic Product
P	Population
PR	Electric Price
HDDs	Heating Degree Days
CDDs	Cooling Degree Days
M_i	Monthly dummy variable of the corresponding month i
r	Pearson correlation coefficient
R^2	Coefficient of determination

countries [4–6]. As for Guangzhou, since Guangzhou has a subtropical climate with hot summers, further climate warming may lead to increases in electricity consumption as more electric energy will be required for cooling. In addition, electricity consumption in Guangzhou is large and increasing due to its fast economic growth and the improvement of people's living standards. Therefore, electricity consumption in Guangzhou could continue to grow with climate warming and socioeconomic development. It is thus urgent that policymakers are able to predict electricity consumption and take adaptive measures in response to this trend.

Previously, the linear regression analysis method has been the most popular modeling techniques in electricity consumption predicting due to the simplicity of application and result explanation [7]. In addition, the heating degree days (HDDs) and the cooling degree days (CDDs) were widely used to estimate the relationships between temperature and electricity consumption [3,8]. They are defined as the number of degrees the temperature falls below or exceeds certain base temperatures [9,10]. For example, Sailor and Pavlova [11] used the regression models to analyze the relationship between CDDs and electricity demand for space cooling in the 39 US cities.

Meanwhile, electricity consumption has been increasing with the development of industry and the improvement of living standards [12]. Mukhopadhyay and Nateghi [13] concluded that additional non-climate variables should be incorporated into the model's structure. Mirasgedis et al. [14] used a regression model to estimate the impact of climate change on electricity consumption in Greece. Apart from the climate variables (i.e., HDDs and CDDs), socioeconomic parameters (i.e., population and GDP) and monthly dummy variables were also employed in their models. The results shown that population and GDP had positive and significant impacts on electricity consumption and the relationship between seasonality and electricity consumption cannot be ignored. Ruth and Lin [7] investigated how temperature increases affect electricity consumption in Maryland using the regression analysis by incorporating the socioeconomic and climate variables. Similar approaches were adopted by Ahmed [15] and Trotter [16].

However, the linear regression analysis is unable to reject the explanatory variables that are not of significance and to address the problem of multicollinearity among the explanatory variables. Consequently, the electricity consumption models might be developed based on variables that are not significantly influential and hide the issue of multicollinearity, creating parameter-identification issues and getting biased results [17,18]. In order to solve the problems of linear regression analysis, the stepwise regression analysis and the best subset regression analysis were widely used [19]. However, previous studies has confirmed that the stepwise regression analysis have many problems such as R^2 values are biased high and p-vaules are biased low [20,21]. Therefore, the best subset regression analysis is selected in this study in order to ensure the reliability of the developed electricity consumption models. The adjusted R^2, p-vaule, and also the multicollinearity degree of inputs are used to find the optimum combination of the independent variables [22]. After fitting and testing all possible combinations of the independent variables, accurate predictive models can be developed by using the best subset regression analysis.

Another research gap from the previous work is in future climate

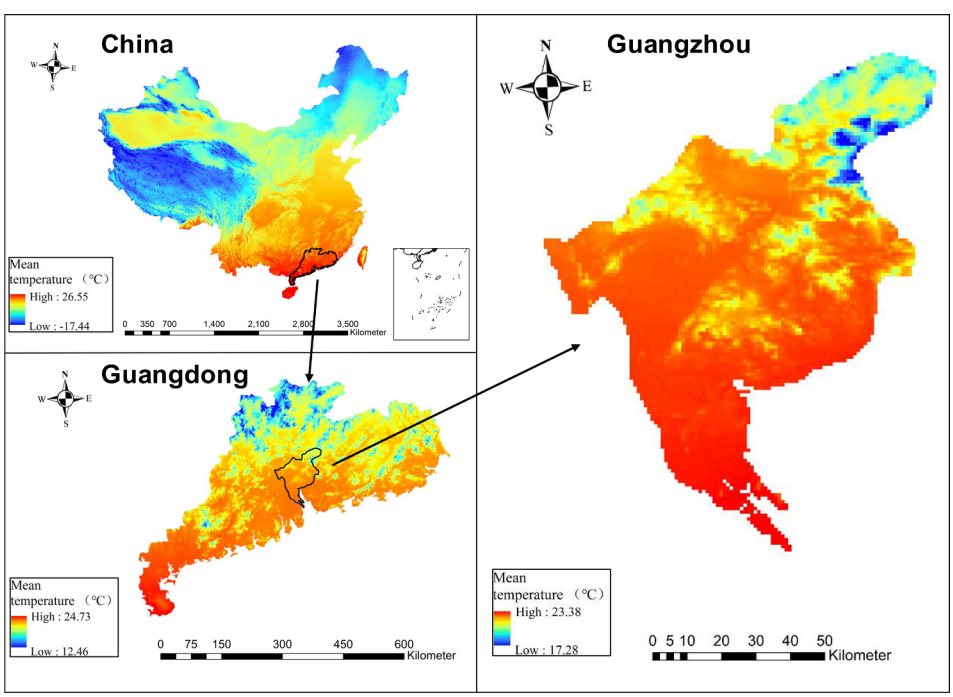

Fig. 1. The location of Guangzhou in China and yearly mean temperature (2001–2015) in China.

Table 1
Representation Concentration Pathways (RCPs).

RCPs	Characteristic	Radiative forcing
RCP2.6	Very low greenhouse gas emission	2.6 W/m^2
RCP4.5	Intermediate stabilization	4.5 W/m^2
RCP6.0	High stabilization	6.0 W/m^2
RCP8.5	Very high greenhouse gas emissions	8.5 W/m^2

Note. RCP2.6 has a peak forcing of 3 W/m^2 before a decline to 2.6 W/m^2.

Table 2
Selected GCMs in this study.

Model name	Institute	Lat. × Lon. (°)
CSIRO-Mk3-6-0	Commonwealth Scientific and Industrial Research Organization in collaboration with the Queensland Climate Change Centre of Excellence	1.8 × 1.8
GFDL-CM3	Geophysical Fluid Dynamics Laboratory	2.0 × 2.5
GFDL-ESM2G		1.5 × 2.5
GFDL-ESM2M		1.5 × 2.5
HadGEM2-AO	Met Office Hadley Centre / INPE	1.2 × 1.8
HadGEM2-ES	Met Office Hadley Centre	1.2 × 1.8
IPSL-CM5A-LR	Institut Pierre-Simon Laplace	1.8 × 3.7
IPSL-CM5A-MR		1.2 × 2.5
MIROC-ESM	Atmosphere and Ocean Research Institute	2.7 × 2.8
MIROC-ESM-CHEM	(The University of Tokyo), National Institute for Environmental Studies, and Japan Agency	2.7 × 2.8
MIROC5	for Marine-Earth Science and Technology	1.3 × 1.4
MRI-CGCM3	Meteorological Research Institute	1.1 × 1.1
NorESM1-M	Norwegian Climate Centre	1.8 × 2.5

projections. There have been few studies that employed the multi-ensemble average of several global climate models (GCMs) in the electricity consumption models [2,7,16]. However, due to the uncertainty of climate model, climate modeling groups under the Coordinated Modelling Intercomparison Project Phase 5 (CMIP5) have applied an ensemble of a number of climate models to estimate the change rate of climate change for each Representative Concentration Pathways (RCPs). In this study, the multi-ensemble average of 13 GCMs under four RCPs will be used to predict future climate conditions, and thus investigate the uncertainties in electricity consumption forecasts [23].

The first major contribution of this study is the development of Guangdong's electricity consumption forecasting models. The best subset regression analysis will be used to develop such models. They can help address the disadvantage of the linear regression analysis and excavate the influence factors of electricity consumption. On the other hand, this study is the first research attempt to quantify the effects of climate change on electricity consumption in Guangzhou, China. Guangzhou has a subtropical climate with hot summers; further climate warming will lead to the increases in electricity consumption as more electric energy will be required for cooling. Policymakers in Guangzhou can obtain reliable electricity consumption forecasts through the proposed electricity consumption models. This study can provide valuable information for decision support under climate change.

The objective of this study is to quantify the effects of climate change on total electricity consumption (TEC) and residential electricity consumption (REC) in Guangzhou. The Mann-Kendall test will be used to explore the climate trend till the end of the 21st century. In addition, Guangzhou's TEC and REC models will be developed based on the best subset regression analysis. The proposed models can further be used to calculate electricity consumption under socioeconomic and climate change and identify the effects of climate change on electricity consumption.

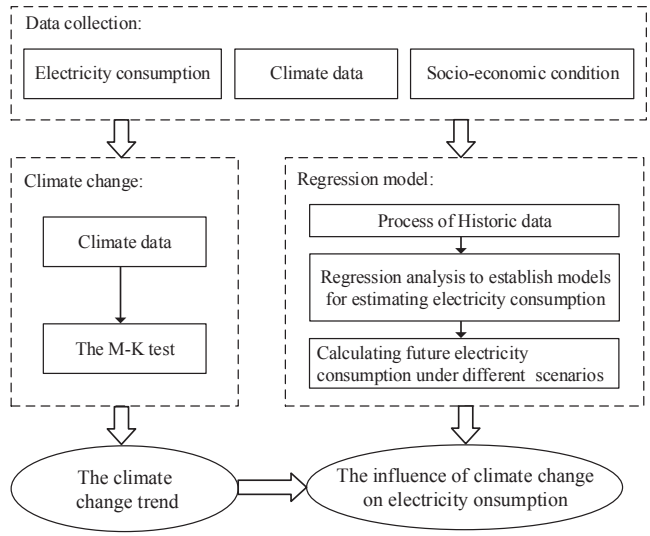

Fig. 2. Methodological process for quantifying climate change and the impacts on electricity consumption.

2. Study area and data collection

Guangzhou (latitude 22°26′ to 23°56′N, longitude 112°57′ to 114°03′E) is the capital of Guangdong Province in China with a total area of 7,434 square kilometers and a population of over 14 million at the end of 2016 (sourced from the statistical yearbooks of Guangzhou). Additionally, Guangzhou is situated at the core area of the Pearl River Delta with a Gross Domestic Product (GDP) of 290.6 billion dollars in 2015. In 2015, the city's TEC and REC were 77.9 TWh and 16.1 TWh, respectively. As shown in Fig. 1, Guangzhou is located in the hot subtropical climate zone with hot summers and mild winters. The mean temperatures of summer and winter are 28.6 and 14.9 °C, respectively.

Electricity consumption data from 2004 to 2015 were obtained from the government website of Guangzhou Statistics Bureau (http://www.gzstats.gov.cn). Electricity price was obtained from the statistical yearbooks of China Electric Power (2005–2016). GDP and population were obtained from the statistical yearbooks of Guangzhou (2005–2016). The historical daily temperatures ranging from 1971 to 2015 were collected from the website of China Meteorological Data Service Center (CMDC) (http://data.cma.cn).

'The rate and magnitude of global climate change are determined by radiative forcing' [1]. Representation Concentration Pathways (RCPs) are developed based on four trajectories of total radiative forcing in the year 2100 relative to 1750 (as shown in Table 1) [24,25]. Climate change over this century under four RCPs was projected by using 13

Table 3
Shared Socio-economic Pathways (SSPs) [27].

SSPs	Characteristic	Challenges
SSP1	Sustainability	Low challenges to mitigation or adaptation
SSP2	Middle of the road	Intermediate challenges
SSP3	Fragmentation	High challenges to both mitigation and adaptation
SSP4	Inequality	Low challenges to mitigation, but high adaptation challenges
SSP5	Conventional development	Low challenges to adaptation, but high mitigation challenges

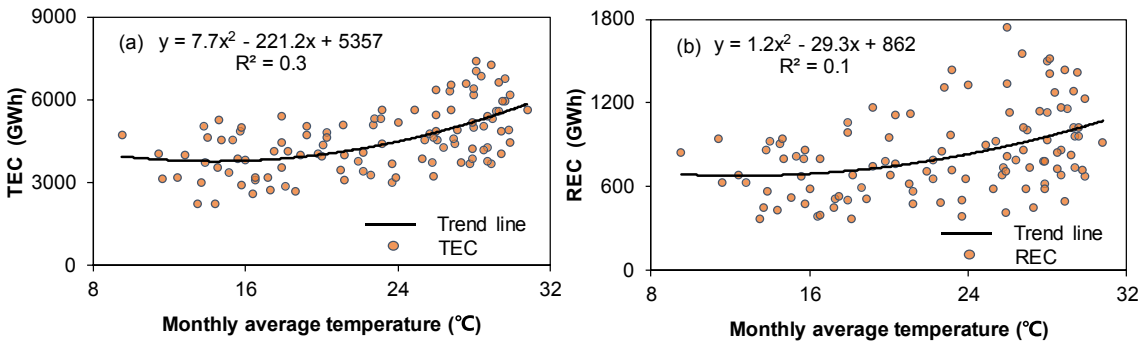

Fig. 3. Correlations between electricity consumptions and temperature [(a) TEC and (b) REC].

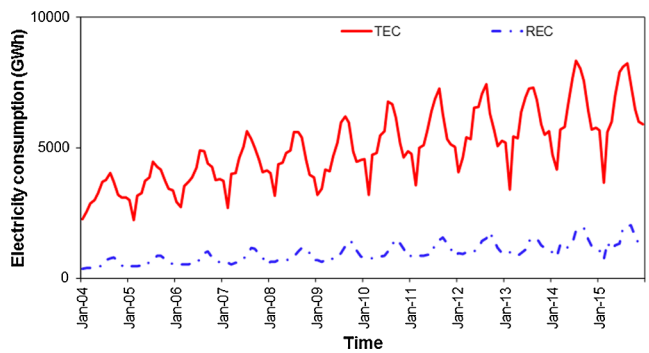

Fig. 4. Monthly electricity consumption data for Guangzhou (2004–2015).

Table 4
Estimated mean temperature, CDDs and HDDs changes in Guangzhou (in °C/decade).

	Mean temperature	CDDs for TEC	CDDs for REC	HDDs for TEC	HDDs for REC
1971–2015(the observed climate date)					
	0.26**	6.59**	6.95**	−0.54	−0.29
1986–2099 (the multi-model ensemble average of 13 GCMs of CMIP5)					
RCP2.6	0.15**	4.04**	4.12**	−0.39**	−0.26**
RCP4.5	0.26**	7.09**	7.29**	−0.71**	−0.48**
RCP6.0	0.26**	7.32**	7.61**	−0.76**	−0.51**
RCP8.5	0.47**	13.08**	13.50**	−1.14**	−0.75**

Trends are detected by the M−K test and estimated by the nonparametric Sen's slops over time (** indicates statistic is significant at the 0.05 level).

Table 5
Correlation of the monthly total electricity consumption and variables.

Variables	Pearson correlation value (r)					
	1	2	3	4	5	6
1. ln GDP	1	–		–	–	–
2. P	0.962***	1		–	–	–
3. PR	0.861***	0.846***	1	–	–	–
4. CDDs	−0.069	−0.052	−0.081	1	–	–
5. HDDs	0.099	0.085	0.121	−0.685***	1	–
6. ln TEC	0.717***	0.702***	0.610***	0.551***	−0.352***	1

*** Correlation is significant at the 0.01 level (2-tailed).

GCMs (Table 2) of CMIP5. All those data were downloaded from the Earth System Grid Federation (ESGF) (http://esgf-node.llnl.gov). As shown in Table 3, the Shared Socio-economic Pathways (SSPs) represent five socioeconomic development pathways [26,27]. In order to estimate GDP, the SSP GDP projections were used. All those data were downloaded from the SSP Database (https://tntcat.iiasa.ac.at/SspDb).

In general, five SSPs and four RCPs can produce 20 (i.e., 5 × 4) scenario combinations that will provide plausible bases for socio-economic and climate change assessment [28]. In order to estimate the change of TEC and REC under different conditions at different times. Four periods were analyzed: the period 1986–2005 (the baseline period), 2016–2035 (the 2030s), 2046–2065 (the 2050s), and 2076–2095 (the 2080s).

Table 6
Correlation between the monthly residential electricity consumption and variables.

Variables	Pearson correlation value (r)					
	1	2	3	4	5	6
1. ln GDP	1	–		–	–	–
2. P	0.962***	1		–	–	–
3. PR	0.607***	0.568***	1			
4. CDDs	−0.072	−0.054	−0.063	1	–	–
5. HDDs	0.093	0.086	0.116	−0.646***	1	–
6. ln REC	0.733***	0.732***	0.457***	0.402***	−0.206**	1

*** Correlation is significant at the 0.01 level (2-tailed).
** Correlation is significant at the 0.05 level (2-tailed).

3. Methodology

The methodological framework is developed and implemented for quantifying the impacts of climate change on regional electricity demand. The framework is depicted in Fig. 2 and comprises five basic stages. First, the climate change trend is analyzed through the Mann-Kendall test. Second, the electricity consumption models are established using the best subset regression analysis. Third, four RCPs (13 GCMs of CMIP5) and five SSPs are used to estimate the future climatic and socioeconomic conditions. Fourth, future electricity consumption is estimated under different climatic and socioeconomic conditions. Fifth, we calculate the percentage change of electricity consumption and the contribution rate of climate change on the change of electricity consumption.

Local climate change trend during the 45-year period (1971–2015) and the trend of the multi-ensemble average of 13 GCMs during the period from 1986 to 2099 are identified using the Mann-Kendall (M-K) test. M-K test is used to test the significance of long-term trends in time series [29,30]. The magnitude of change is estimated using Sen's slops [31]. M-K test and Sen's slops have been widely used in environmental science because these tests are nonparametric and do not assume the distribution form of the data [32]. The M-K test is based on the test statistic S:

$$S = \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} sgn(x_j - x_i) \tag{1}$$

where x_j and x_i are two adjacent values in time series with the length of n for each grid. We test the null hypothesis that the observations are

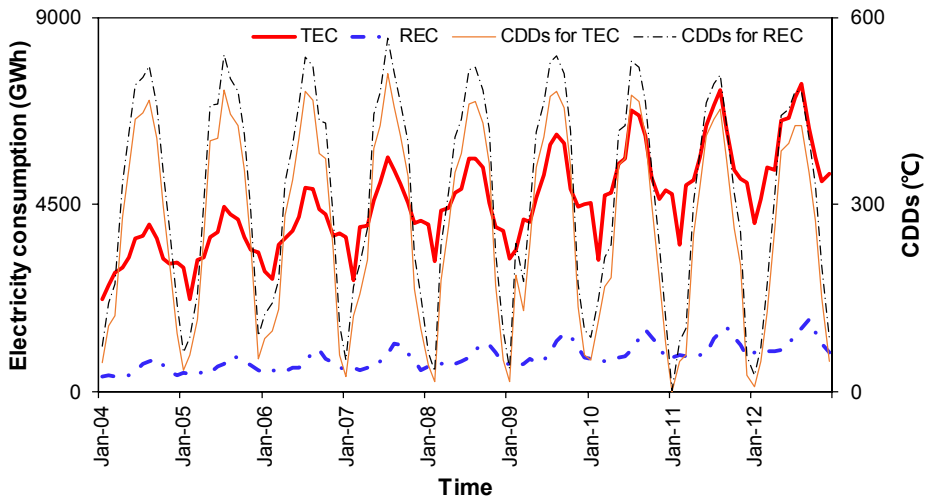

Fig. 5. Relationships between electricity consumption and CDDs.

Table 7
HEGY test for seasonal unit roots, with intercept, monthly dummies, and trend, for the period from January 2004 to December 2012.

H_0	ln TEC		ln REC	
	statistic	*p*-vaule	statistic	*p*-vaule
$\pi_1 = 0$	$T = -2.1$	0.36	$T = -2.7$	0.14
$\pi_2 = 0$	$T = -3.6$	0.003***	$T = -2.8$	0.025**
$\pi_3 = \pi_4 = 0$	$F = 8.2$	0.005***	$F = 4.3$	0.098*
$\pi_5 = \pi_6 = 0$	$F = 10.2$	0.001***	$F = 5.2$	0.051*
$\pi_7 = \pi_8 = 0$	$F = 16.1$	0.000***	$F = 8.1$	0.006***
$\pi_9 = \pi_{10} = 0$	$F = 12.1$	0.000***	$F = 5.6$	0.038**
$\pi_{11} = \pi_{12} = 0$	$F = 17.1$	0.000***	$F = 9.7$	0.002***

*** Statistic is significant at the 0.01 level.
** Statistic is significant at the 0.05 level.
* Statistic is significant at the 0.1 level.

randomly ordered versus the alternative of monotone trend over time. A standard normal variable value Z is then determined and is related to a p-value for a specific trend [33].

Electricity consumption has close relationships with socioeconomic variables (e.g., GDP, population and electricity price) and climatic variables (e.g., temperature) [15]. GDP can be used as the key determinant of electricity consumption because socioeconomic activities consume a certain amount of electric power [14]. The population is also a driver for estimating electricity consumption [15]. Price is generally considered as one of the main determinants of demand. Electricity consumption is inversely correlated with the electricity price [7]. Fig. 3 presents the relationship between electricity consumption and mean

Table 9
The Augmented Dickey Fuller (ADF) unit root test on the considered variables.

Variables	ADF test statistic	10% critical value	Test equation
TEC			
ln TEC	5.4244	−1.6145	None
ln GDP	1.1912	−1.6145	None
CDDs	−0.9961	−1.6145	None
First difference			
ln TEC	−9.3018*	−3.1546	Constant + trend
ln GDP	−1.8539*	−1.6145	None
CDDs	−9.7138*	−1.6145	None
REC			
ln REC	−2.8319	−3.1546	Constant + trend
ln GDP	1.1912	−1.6145	None
CDDs	−0.9989	−1.6145	None
First difference			
ln REC	−10.9868*	−2.5830	Constant
ln GDP	−1.8539*	−1.6145	None
CDDs	−9.8663*	−1.6145	None

* Statistic is significant at the 0.1 level.

Table 10
Summary of the Engle-Granger test.

Variables	EG test statistic	5% critical value	Test equation
TEC	−10.5251**	−1.9439	None
REC	−8.0742**	−1.9439	None

** Statistic is significant at the 0.05 level.

Table 8
The developed models for electricity consumption for the period from January 2004 to December 2012.

TEC ($Adj.R^2 = 0.955$)					REC ($Adj.R^2 = 0.958$)				
Variable	Estimate	Sig.	VIF	Adj.R^2	Variable	Estimate	Sig.	VIF	Adj.R^2
Constant	11.4629	0.000			Constant	8.3878	0.000		
ln GDP	0.5360	0.000	1.0	0.509	ln GDP	0.7371	0.000	1.0	0.533
CDDs	0.0009	0.000	2.8	0.364	CDDs	0.0003	0.000	2.0	0.208
M_2	−0.1899	0.000	1.3	0.052	M_7	0.2583	0.000	1.5	0.027
M_3	0.0535	0.014	1.2	0.002	M_8	0.4535	0.000	1.5	0.053
M_7	0.0851	0.000	1.4	0.003	M_9	0.5461	0.000	1.3	0.057
M_8	0.1013	0.000	1.4	0.004	M_{10}	0.4206	0.000	1.2	0.042
M_9	0.0658	0.003	1.3	0.004	M_{11}	0.2798	0.000	1.0	0.038
M_{12}	0.1377	0.000	1.4	0.017					

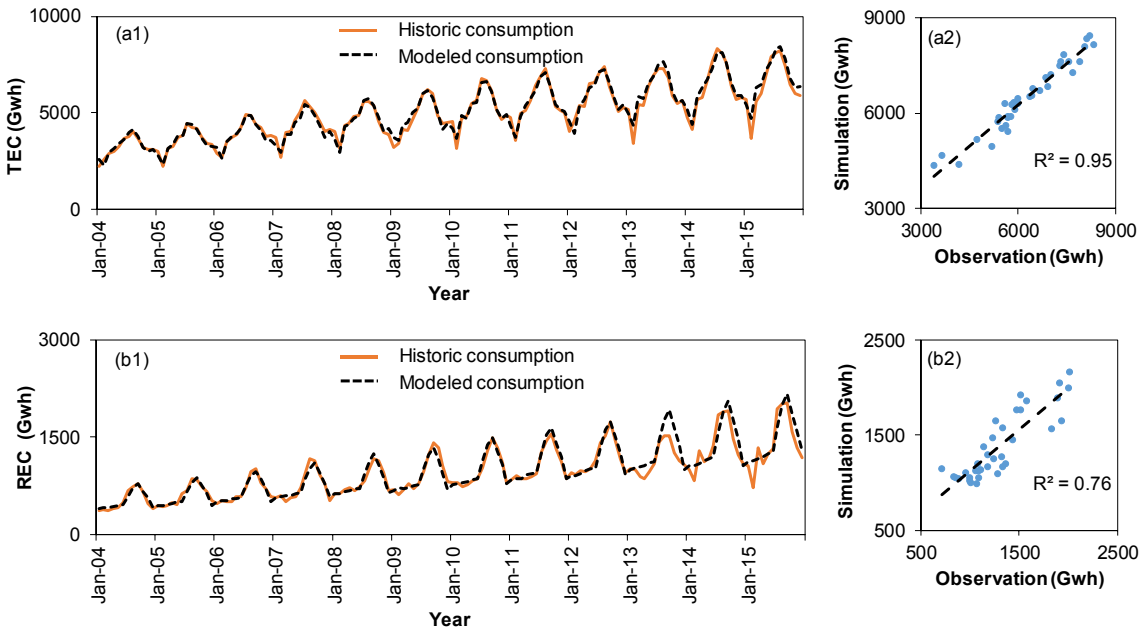

Fig. 6. Model-calculated value and historical electricity consumption value [(a1) TEC and (b1) REC]. The R^2 of the year from 2013 to 2015 [(a2) TEC and (b2) REC].

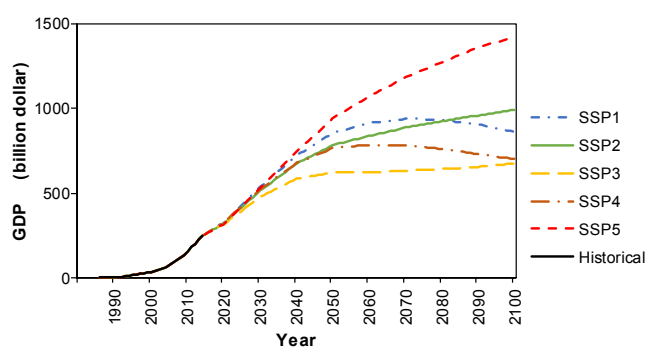

Fig. 7. GDP of Guangzhou under the Shared Socio-economic Pathway scenarios.

Table 11
The average GDP of Guangzhou under SSPs (billion dollar).

	Baseline	SSP1	SSP2	SSP3	SSP4	SSP5
Historical	25					
The 2030s		443	427	403	433	439
The 2050s		880	810	622	771	1007
The 2080s		915	943	650	744	1317

temperature during the period from 2004 to 2012. Just as shown in Fig. 3, the consumption-temperature relationship is non-linear. In order to replace the non-linear relationship to a linear one, the heating degree days (HDDs) and the cooling degree days (CDDs) are used [12]. Based on that, *HDDs* and *CDDs* are calculated as:

$$HDDs = \sum_{d=1}^{Nd} (1 - \gamma_d)(T_b - T_d) \tag{2}$$

and

$$CDDs = \sum_{d=1}^{Nd} (\gamma_d)(T_d - T_b) \tag{3}$$

where γ_d takes on a value of 1 if the mean daily temperature is higher than the base, and zero otherwise; N_d is the number of days in a particular month; T_d is the mean daily temperature; T_b is the base temperature, which has been selected to be equal to 14.3 °C for TEC, and 12.5 °C for REC as the consumption-temperature relationship (as shown in Fig. 3).

Apart from the above socioeconomic and climate variables, monthly dummy variables are considered in the regression analysis. Fig. 4 shows the trends of electricity consumption in Guangzhou. It can be seen that each trend upwards with strong seasonality. Seasonality is mostly caused by varying economic activities [14]. Monthly dummy variables have been used to model the seasonality in several studies under the assumption that the seasonality in a time series is deterministic [34]. HEGY-test can be used to measure whether seasonality in a time series is deterministic or stochastic by identifying whether a time series has a unit roots both in the zero frequency and seasonal frequencies. If the observations have unit roots in the seasonal frequency, seasonality will not be deterministic and monthly dummy variables should not be used [35].

The socioeconomic variables (i.e., GDP, population and electricity price), climatic variables related to temperature (i.e., CDDs and HDDs) and monthly dummy variables are included in the best subset regression analysis. Electricity consumption and GDP are specified in natural log format to reduce heteroscedasticity and reflect the elastic relationship between the variables [7]. The output coefficients for the independent variables can present the percentage change in electricity consumption associated with a unit change in the independent variable [34]. The overall function for estimate electricity consumption can be represented as below:

$$ln\ E_t = a + b{\cdot}ln\ GDP_t + c{\cdot}P_t + d{\cdot}PR_t + e{\cdot}CDD_t + f{\cdot}HDD_t + \sum_{i=2}^{12} a_i{\cdot}M_{it} + e_t \tag{4}$$

where a, b, c, d, e, f and a_i (i from 2 to *12*) are the output coefficients; e_t is the residual term; E_t denotes the electricity consumption in the month t; GDP_t, P_t, and PR_t denotes the production, population, and electricity price during the month t; CDD_t, HDD_t denotes the cooling, heating degree days in the month t; M_{it} is the monthly dummy variables. The index i values in the interval representing corresponding all month in a year ($i = 2$ for February, $i = 3$ for March,… $i = 12$ for December) except for the base month of January. Correspondingly, M_{it} are defined as below: M_{2t} is equal to 1 if the observation is for February and zero otherwise,

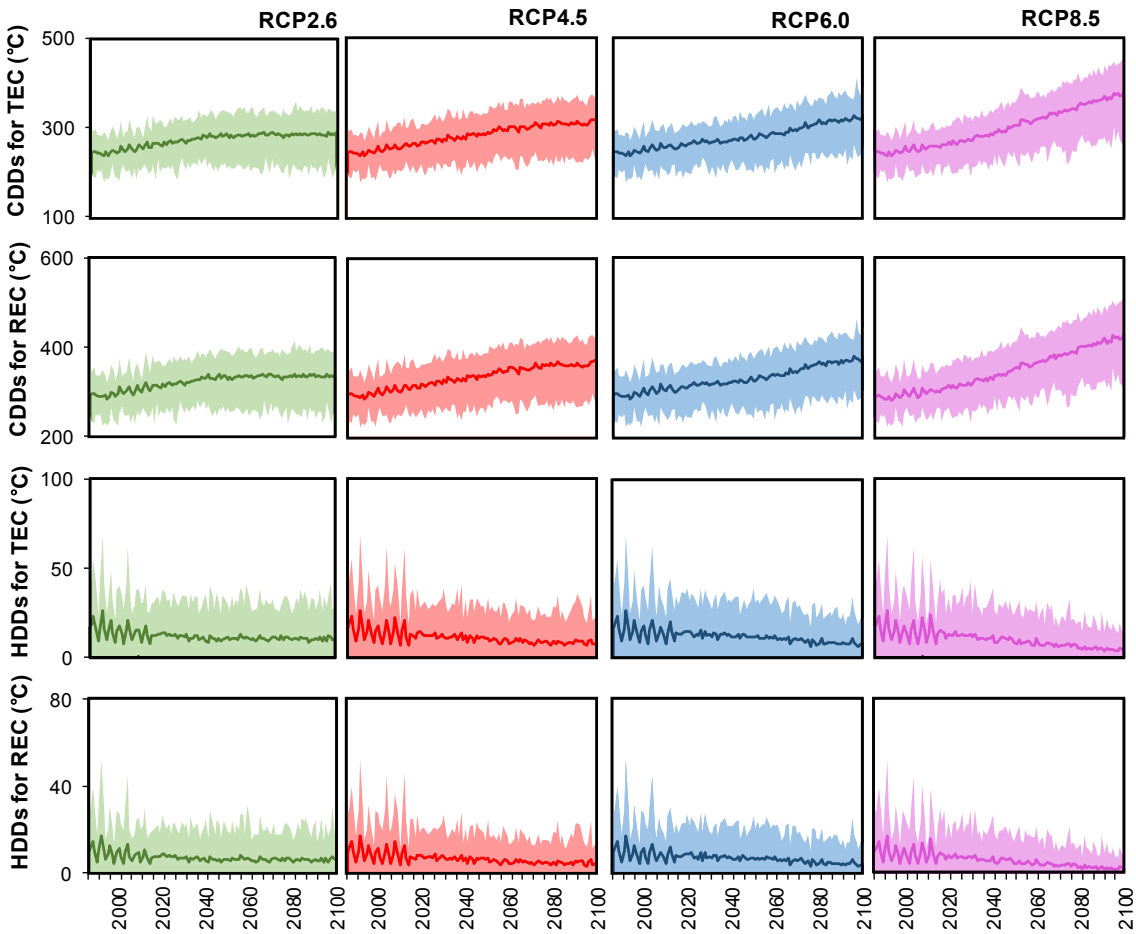

Fig. 8. Change of CDDs and HDDs in Guangzhou under the four RCPs. The thick line shows the ensemble mean of 13 GCMs for each RCP.

Table 12
The average CDDs of Guangzhou under RCPs (°C).

	Baseline	RCP2.6	RCP4.5	RCP6.0	RCP8.5
CDDs for TEC					
Historical	247				
The 2030s		268	270	266	270
The 2050s		283	294	282	312
The 2080s		285	309	314	358
CDDs for REC					
Historical	296				
The 2030s		318	320	316	320
The 2050s		334	345	329	363
The 2080s		335	360	366	410

M_{3t} is equal to 1 if the observation is for March and zero otherwise, and so on.

4. Result analysis

4.1. Climate change trends

Table 4 shows the results of the M-K test. For the observed temperature (from 1971 to 2015), mean temperature and the CDDs increased and the HDDs decreased in Guangzhou. The trend of mean temperature and the average CDDs were highly significant ($p < 0.01$). The mean temperature increased with a rate of 0.257 °C/decade during the 45-year period. The result suggests that the climate became warmer over the past 45 years. Since the warmer of climate, the average CDDs increased with a rate of 6.587 °C/decade (for TEC) and 6.950 °C/decade (for REC). It suggests that the electricity demand for cooling was significantly increasing with climate warming.

As for the M-K test results of the multi-ensemble average of 13 GCMs during the period from 1986 to 2099, mean temperature and CDDs will significantly increase and HDDs will significantly decrease at a different rate under four RCPs. Under RCP2.6, the changing rate is the lowest, while RCP8.5 is the highest and RCP4.5 has similar rate with RCP6.0. These results suggest that climate warming and cooling electricity demand increasing will continue in Guangzhou. In addition, climate scenarios can affect the increasing rate of mean temperature and the average CDDs.

4.2. Correlation analysis results

Tables 5 and 6 were obtained from the correlation analysis. ln GDP and P have a strong positive correlation with electricity consumption. CDDs has a positive correlation with electricity consumption. In addition, Fig. 5 shows the relationship between electricity consumption and CDDs. These results suggest that electricity consumption will increase with climate warming. PR has a positive correlation with electricity consumption, meaning that electricity consumption is not significantly influenced by the electricity price [36]. HDDs has a negative correlation with electricity consumption. As climate warming, there were fewer HDDs, yet TEC and REC increased. This phenomenon suggests that electricity consumption in Guangzhou were insignificantly influenced by HDDs [37]. In addition, several variables, such as ln GDP and P, CDDs and HDDs show significant inter-correlations between two variables. This result suggests that the collinearity exists between independent variables.

Table 7 shows the results of the HEGY test. Only the first hypothesis $t_{\pi 1}$ was accepted at the 10% level of significance. This result suggests

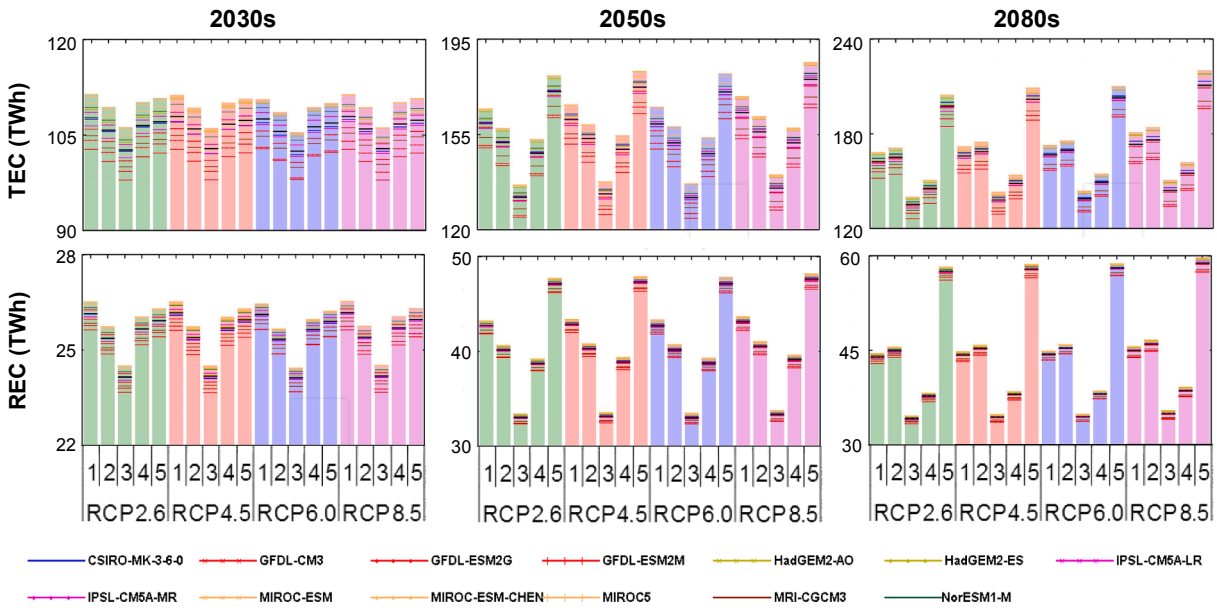

Fig. 9. Change of TEC and REC in Guangzhou, under the four RCPs and five SSPs. The ensemble mean for each situation is shown by the black line.

that the time series of electricity consumption had unit roots at the zero frequency and there was no evidence of unit roots at the seasonal frequencies. Seasonality in time series was tested to be deterministic. Thus, monthly dummy variables can be used to model the seasonality of the time series [34].

4.3. Regression analysis results

The models for TEC and REC were developed by the best subset regression analysis using 108 monthly observations (from January 2004 to December 2012). The processes of establishing those models were shown in the appendix (Tables A1 and A2). The final regression models were shown in Table 8.

The variabilities of electricity consumption explained by the corresponding variables were shown in Table 8. The variability of electricity consumption explained by ln GDP is the highest, suggesting that electricity consumption is primarily affected by socioeconomic conditions. CDDs is included in the equation, showing the influence of hot temperature on electricity consumption. The established models also show the strong influence of the monthly dummy variables on electricity consumption. In detailed, February, March, July, August, September, December are included in the TEC model. Except for February, all coefficients for the above months are positive. This result shows that more electric energy is consumed during the corresponding months excluding February than in January. The coefficients for February is negative, suggesting that TEC is expected to decrease during the Spring Festival holiday. For REC, the coefficient for July, August, September, October, November are positive and significant, showing that more electric energy is consumed during the corresponding months than in January.

There are some differences between the developed TEC and REC model. The variabilities of TEC and REC explained by ln GDP are 50.9%, 53.3%, respectively. A 1% change in GDP will change TEC by 0.54% and 0.74% for REC. These results suggest that REC is more sensitive to socioeconomic variables than TEC. The variabilities of TEC and REC explained by CDDs are 36.4%, 20.8%, respectively. A one-unit change in CDDs will change TEC and REC by 0.09% and 0.03%, respectively. If the temperature warms up 1 °C in one summer month with 30 days, TEC and REC will increase by 2.7% and 0.9%, respectively. These results suggest that TEC is more sensitive to climatic variables than REC. What more, the variability of REC explained by dummy variables is 21.7%, which is higher than TEC (8.2%), suggesting that the influence of seasonality on REC is more obvious than on TEC.

The Augmented Dickey Fuller (ADF) test was used to test the null hypothesis that the series is a unit root. The Engle-Granger test was used to further test for co-integration of the series. Table 9 shows the results of the ADF test. The results show that the null hypothesis cannot be rejected at 10% level of significance, indicating that the series is a unit root. Stationarity was obtained by running the ADF test on the first difference, indicating that the series of all variables are I(1). Table 10 shows the results of the Engle-Granger test [38]. The results show that the series of dependent and the independent variables are co-integrated. Fig. 6 shows the simulation results of the TEC and REC models in calibration (2004–2012) and validation (2013–2015) periods. There are good agreements between the observed and the predicted electricity consumption in training and testing periods (as shown in a1 and b1). The determination coefficient (R^2) for testing periods is 0.95 for the TEC model and 0.76 for the REC model (as shown in a2 and b2). The variance inflation factor (*VIF*) shows that collinearity was not found among predictors [39]. All the predictors are significant (as shown in Table 8). Therefore, the developed models are applicable to forecast electricity consumption [40].

4.4. Future socioeconomic and climate conditions

Fig. 7 shows the SSPs GDP projections in Guangzhou. Before 2040, the differences between SSPs will be more modest than the years after 2040. The average value of GDP under SSPs was shown in Table 11. The lowest GDP is always under SSP3, while the highest is under SSP1 in the 2030s and under SSP5 in the 2050s and 2080s. In addition, in the 2080s, GDP under SSP5 is obviously higher than others. The average value of GDP will increase except SSP4, which will decline in the 2080s.

The interval of degree days of 13 GCMs and the mean value of those GCMs under four RCPs were shown in Fig. 8. Degree days for TEC and REC are shown the same tendency: CDDs are increasing, while HDDs are decreasing. These results suggest that the temperature in Guangzhou will increase throughout the end of the 21st century. Before 2030, there are little differences between all RCPs. After 2030 the differences between all RCPs are becoming obvious and RCP8.5 are higher than other RCPs, obviously. The average value of CDDs under RCPs was shown in Table 12. CDDs under RCP8.5 is the highest. CDDs under RCP4.5 is higher than RCP2.6. In the period of the 2030s and the 2050s,

Table 13
The ensemble mean of electricity consumption for 13 GCMs under the four RCPs and five SSPs. The interval of 13 GCMs is shown in the bracket.

	SSP1	SSP2	SSP3	SSP4	SSP5
a1) Total electricity consumption (TWh): 2030s					
RCP8.5	107.9	105.9	102.9	106.7	107.3
	(103–111)	(101–109)	(98–106)	(102–110)	(102–111)
RCP6.0	107.5	105.5	102.5	106.3	106.9
	(103–111)	(101–109)	(98–105)	(102–109)	(102–110)
RCP4.5	107.9	105.9	102.9	106.7	107.3
	(103–111)	(101–109)	(98–106)	(102–110)	(102–111)
RCP2.6	107.7	105.7	102.7	106.5	107.1
	(103–111)	(101–109)	(98–106)	(102–110)	(102–111)
a2) Total electricity consumption (TWh): 2050s					
RCP8.5	163.1	155.9	135.3	151.9	175.1
	(153–169)	(147–162)	(127–140)	(143–157)	(165–181)
RCP6.0	158.8	151.9	131.8	148.0	170.6
	(150–165)	(143–158)	(124–137)	(139–154)	(161–177)
RCP4.5	160.5	153.4	133.2	149.5	172.3
	(151–166)	(145–159)	(126–138)	(141–155)	(163–178)
RCP2.6	158.9	151.9	131.9	148.1	170.7
	(150–164)	(143–157)	(125–136)	(140–143)	(161–177)
a3) Total electricity consumption (TWh): 2080s					
RCP8.5	173.2	176.1	144.2	155.0	210.6
	(161–181)	(164–184)	(134–151)	(144–162)	(196–220)
RCP6.0	166.8	169.5	138.8	149.3	202.7
	(157–173)	(159–176)	(131–144)	(140–155)	(191–210)
RCP4.5	165.9	168.7	138.1	148.5	201.7
	(155–172)	(158–175)	(129–143)	(139–154)	(189–209)
RCP2.6	162.4	165.1	135.2	145.4	197.5
	(152–168)	(154–171)	(126–140)	(136–151)	(185–204)
b1) Residential electricity consumption (TWh): 2030s					
RCP8.5	25.5	24.8	23.8	25.1	25.3
	(25–26)	(24–25)	(23–24)	(25–26)	(25–26)
RCP6.0	25.4	24.8	23.8	25.0	25.2
	(25–26)	(24–25)	(23–24)	(25–25)	(25–26)
RCP4.5	25.5	24.8	23.8	25.1	25.3
	(25–26)	(24–25)	(23–24)	(25–25)	(25–26)
RCP2.6	25.5	24.8	23.8	25.1	25.3
	(25–26)	(24–25)	(23–24)	(25–25)	(25–26)
b2) Residential electricity consumption (TWh): 2050s					
RCP8.5	43.1	40.5	33.4	39.1	47.6
	(42–44)	(40–41)	(33–34)	(38–40)	(47–48)
RCP6.0	42.7	40.1	33.0	38.7	47.1
	(42–43)	(39–41)	(32–34)	(38–39)	(46–48)
RCP4.5	42.8	40.3	33.2	38.9	47.3
	(42–43)	(39–41)	(32–34)	(38–39)	(46–48)
RCP2.6	42.7	40.1	33.0	38.7	47.1
	(42–43)	(39–41)	(32–33)	(38–39)	(46–48)
b3) Residential electricity consumption (TWh): 2080s					
RCP8.5	45.0	46.0	34.9	38.6	58.8
	(44–46)	(45–47)	(34–35)	(38–39)	(57–60)
RCP6.0	44.3	45.4	34.5	38.1	58.0
	(43–45)	(44–46)	(34–35)	(37–39)	(57–59)
RCP4.5	44.3	45.3	34.4	38.0	57.9
	(43–45)	(44–46)	(34–35)	(37–38)	(57–59)
RCP2.6	43.9	44.9	34.1	37.7	57.5
	(43–45)	(44–46)	(33–35)	(37–38)	(56–58)

CDDs under RCP6.0 is just lower than RCP2.6, while in the 2080s, RCP6.0 is higher than RCP4.5. CDDs under RCP8.5 is always the highest; CDDs under RCP6.0 is the lowest in the 2030s and the 2050s, while in the 2080s, the lowest is under RCP2.6.

4.5. Electricity consumption prediction

Fig. 9 and Table 13 show the corresponding TEC and REC in the 2030s, 2050s, and 2080s, considering the impact of climate change and socioeconomic development. Under different conditions, the trend of REC is the same as TEC.

There are differences in electricity consumption between 13 GCMs. The interval of electricity consumption under 13 GCMs was shown in the bracket of Table 13. For instance, under SSP2 and RCP8.5, TEC is between 101 and 109 TWh in the 2030s. With time, the variability becomes larger, since the variability between different GCMs is getting larger. According to IPCC's reports, variation across different GCMs is greater than variation across different RCPs, considerably [1]. In order to remove the uncertainty of the climate models, the multi-ensemble average was used to predict future climatic conditions. In the following section, the multi-ensemble average of 13 GCMs was used to predict future electricity consumption.

SSPs have varied implications for electricity consumption under a given RCP. Under SSPs, the trend of electricity consumption is the same as the trend of GDP. Under SSP3, electricity consumption is always the lowest, while the highest is SSP1 in the 2030s and SSP5 in the 2050s and 2080s. In addition, in the 2050s and 2080s, SSP5 are obviously higher than other SSPs. Electricity consumption is expected to increase except SSP4, which will decline in the 2080s.

Results also show that RCPs have varied implications for electricity consumption under a given SSP. A higher radiative forcing means a warmer temperature and then a higher increase in CDDs. The results of correlation analysis and the regression analysis show that electricity consumption has a positive correlation with CDDs. The trend of electricity consumption is the same as the trend of CDDs in the future. A higher increase in CDDs will lead to a higher increase in electricity consumption. In the 2080s, as the radiative forcing grows, more electricity would be used for cooling in Guangzhou under RCP8.5 than other RCPs. There is a little clear difference in electricity consumption between all RCPs in the 2030s and between RCP2.6, RCP4.5 and RCP6.0 in the 2050s and between RCP4.5 and RCP6.0 in the 2080s. Under RCP4.5, electricity consumption is higher than RCP2.6. In the 2030s, electricity consumption under RCP6.0 is just less than RCP2.6; In the 2050s, RCP6.0 and RCP2.6 produce very similar impacts, while in the 2080s RCP6.0 is higher than RCP2.6 even higher than RCP4.5. Under RCP8.5, electricity consumption is the highest and in the 2050s and 2080s are clearly higher than other RCPs. In the 2030s and 2050s, electricity consumption is lowest under RCP6.0; in the 2080s, the lowest is under RCP2.6.

Figs. 10 and 11 show the percentage change of electricity consumption and the contribution rate of climate change under different conditions. For TEC, the trend of the percentage change of electricity consumption attributable to socioeconomic and climate change are the same as the trend of electricity consumption under SSPs. In order to study the impact of climatic change on electricity consumption, the percentage change attributable to climate change was analyzed. In addition, the trend is the same as the trend of electricity consumption under RCPs. In order to understand the magnitude of the influence of climate change on electricity consumption, the contribution rate of climate change was analyzed. The trend of the contribution rate under RCPs × SSPs is the same as the trend of change attributable to climate change. In addition, the value of the contribution rate has an inverse relationship with the change attributable to socioeconomic change under a given RCP. The reason is that the ratio of variations between RCPs is higher than between SSPs.

Table 14 shows the integrated results of the variability of GDP, CDDs and electricity consumption under different conditions. The variability between the maximum and minimum and the corresponding scenarios can be found in Table 14. Over time, the variability of electricity consumption becomes larger since the variability of GDP and CDDs gets larger. Figs. 9–11 and Table 14 show that the variations of electricity consumption between SSPs are greater than that across RCPs. The trend under different SSPs × RCPs conditions is the same as the trend under different SSPs. The reason is that electricity consumption is more sensitive to socioeconomic variables than climatic variables and the increase in GDP is greater than the increase in CDDs.

As mentioned above, the trend of REC is the same as TEC under different conditions. Notably, there are some differences between TEC and REC. Figs. 10 and 11 and Table 14 show that the percentage change of REC is bigger than TEC. The reason is that REC is more sensitive to socioeconomic variables than TEC. As the increasing rate of REC is

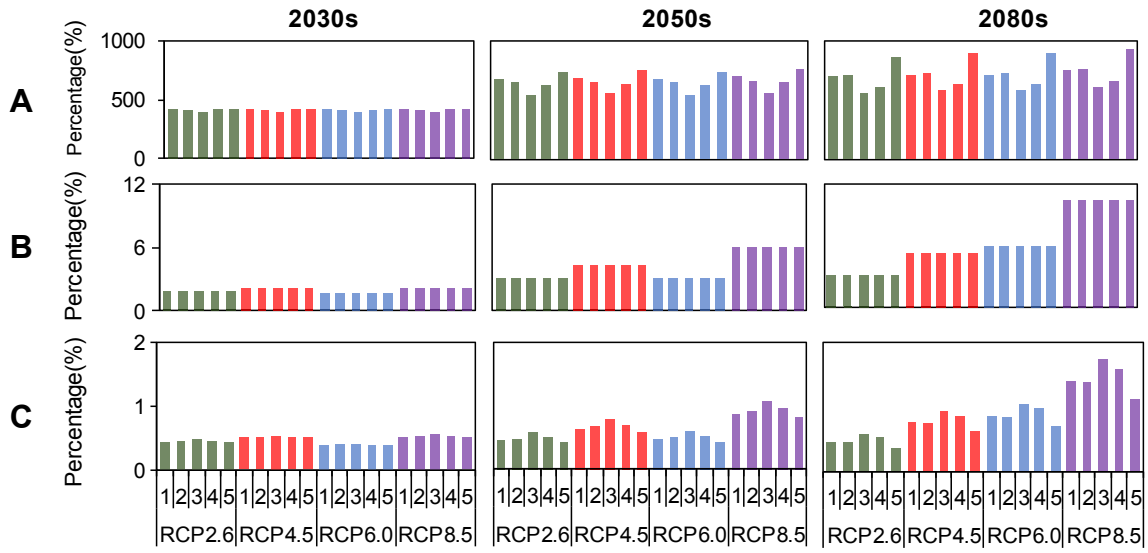

Fig. 10. Percentage change of TEC under different conditions and the contribution rate of climate change-induced TEC variation [A: change attributable to socioeconomic and climate change; B: change attributable to climate change; C: the contribution rate of climate change].

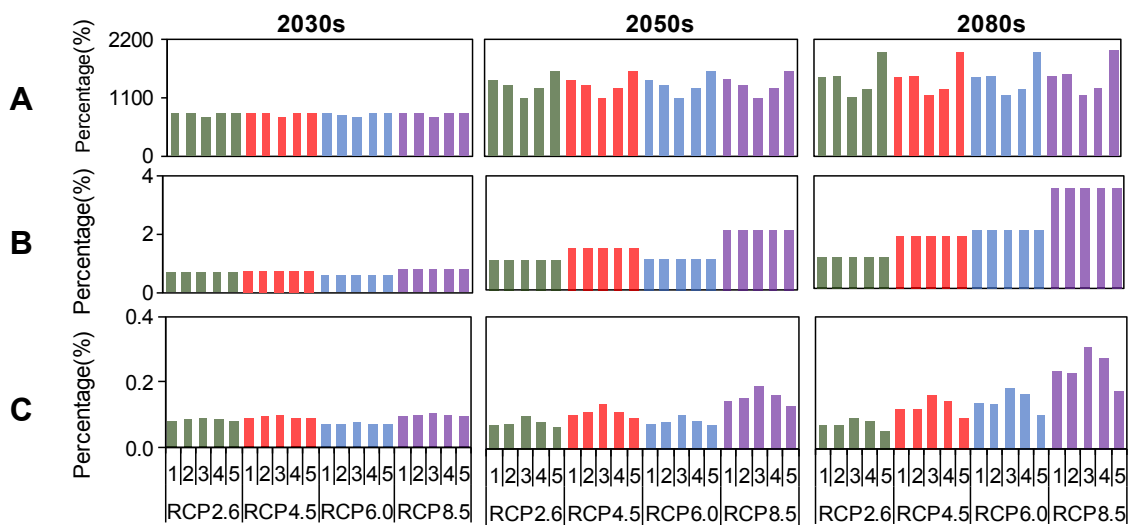

Fig. 11. Percentage change of REC under different conditions and the contribution rate of climate change-induced REC variation [A: change attributable to socioeconomic and climate change; B: change attributable to climate change; C: the contribution rate of climate change].

bigger than TEC, the proportion of REC to TEC will increase in the future. The proportion will reach 23.5%, 26.2% and 26.4% in the 2030s, 2050s and 2080s, respectively. Figs. 10 and 11 and Table 14 show that the percentage change of REC attributable to climate change and the contribution rate of climate change are lower than TEC. The reason is that TEC is more sensitively associated with climatic variables than REC. Above all, those results indicate that REC is more sensitive to socioeconomic variables than TEC, and climatic variables have more obvious influence on TEC than on REC.

5. Discussion

The best subset regression analysis was used to develop electricity consumption models. GDP and CDDs are included in the developed models. This result indicates that GDP and CDDs are the driving factors of the increasing of TEC and REC in Guangzhou. In addition, GDP is more sensitive to electricity consumption than CDDs. This result indicates that the increase in electricity consumption is mainly caused by the overall growth of social and economic activities and the improvement of people's living standards. This conclusion can be verified by the results of the studies by Fan et al. [41] and Mirasgedis et al. [14]. They all concluded that electricity demand is primarily affected by socioeconomic variables.

The result indicates that the population is not the driving factor of the increasing of TEC and REC in Guangzhou. The reason is that the increase in electricity consumption is mainly caused by the overall growth of social and economic activities and the improvement of people's living standards instead of population. Such results are also affirmed by previous studies. For example, Trotter et al indicated that there is direct link between social productive activity and TEC [34]. Nie and Kemp [42] further indicated that the increases in China's REC mainly caused by the increase in energy-using appliances and the increase in floor space per capita.

The results of this study demonstrate that the electricity price is not necessary for the developed models. The reason is that the electricity price in China was determined by the government rather than the supply and demand relationship [43] and the influence of electricity price on electricity consumption is limited [36]. Such results are also affirmed by previous studies. For example, Ahmed et al. [15] indicated that electricity consumption is not significantly influenced by the

Table 14
The maximum, minimum and the differences of GDP (billion dollar), CDDs (°C) and electricity consumption (TWh) under different conditions. The corresponding conditions are placed under the corresponding items.

Variables		2030s			2050s			2080s		
		Mini.	Max.	Diff.	Mini.	Max.	Diff.	Mini.	Max.	Diff.
TEC	GDP	403 3	443 1	40	622 3	1007 5	385	650 3	1317 5	667
	CDDs	266 6.0	270 8.5	4	282 6.0	312 8.5	30	285 2.6	358 8.5	73
	A	103 3	108 1	5	133 3	172 5	39	139 3	203 5	64
	B	105.8 6.0	106.1 8.5	0.3	152 6.0	156 8.5	4	161 2.6	172 8.5	11
	C	103 3–6.0	108 1–8.5	5	132 3–6.0	175 5–8.5	43	135 3–2.6	211 5–8.5	76
	D	400 3–6.0	426 1–8.5	26	543 3–6.0	754 5–8.5	211	560 3–2.6	927 5–8.5	367
	E	1.7 6.0	2.2 8.5	0.5	3.1 6.0	6.1 8.5	3	3.2 2.6	10.4 8.5	7.2
	F	0.40 1–6.0	0.55 3–8.5	0.15	0.42 5–6.0	1.08 3–8.5	0.66	0.38 5–2.6	1.72 3–8.5	1.34
REC	GDP	403 3	443 1	40	622 3	1007 5	385	650 3	1317 5	667
	CDDs	316 6.0	320 8.5	4	329 6.0	364 8.5	35	335 2.6	410 8.5	75
	A	24 3	26 1	2	33 3	47 5	14	35 3	58 5	23
	B	24.8 6.0	24.9 8.5	0.1	40 6.0	41 8.5	1	44 2.6	47 8.5	3
	C	24 3–6.0	26 1–8.5	2	33 3–6.0	48 5–8.5	15	34 3–2.6	59 5–8.5	25
	D	750 3–6.0	810 1–8.5	60	1080 3–6.0	1598 5–8.5	518	1119 3–2.6	2000 5–8.5	881
	E	0.6 6.0	0.8 8.5	0.3	1.0 6.0	2.1 8.5	1.1	1.1 2.6	3.5 8.5	2.4
	F	0.07 1–6.0	0.10 3–8.5	0.03	0.07 5–6.0	0.20 3–8.5	0.13	0.05 5–2.6	0.31 3–8.5	0.26

A: the average electricity consumption under five SSPs; B: the average electricity consumption under four RCPs; C: the electricity consumption under five SSPs and four RCPs; D: the percentage change of electricity consumption under five SSPs and four RCPs; E: the percentage change of electricity consumption under four RCPs; F: the contribution rate of climate change-induced electricity consumption variation under five SSPs and four RCPs.

electricity price in the State of New South Wales, Australia. Fan et al. [41] concluded that the effect of electricity price on electricity consumption was insignificant in China, which reflect the rigid demand of electricity consumption on electricity price. Moreover, our results suggest that HDDs should not be considered in the proposed model, since Guangzhou has a subtropical climate with hot summers and mild winters, and thus the demand for heating is small. It is also consistent with the results in the study of Pilli-Sihvola et al. [34], which concluded that the impacts of climate warming on electricity consumption depending on the geographic location of the study area.

Both TEC and REC will increase with warming temperature in Guangzhou. In addition, electricity consumption could vary significantly under four RCPs. As the radiative forcing grows, more electricity would be used for cooling in Guangzhou under RCP8.5 than other RCPs. Considering the future socioeconomic change, compared with RCP2.6, TEC will rise by 11 TWh under RCP8.5 in the 2080s, accounting for 13% of TEC in Guangzhou in 2017. Those results indicate that climate policies tend to significantly affect electricity consumption. If there is a lack of climate policy intervention, more electric energy will be used to meet the rising cooling demand. The intention proclaimed by the Paris Climate Agreement is to 'holding the increase in global average temperature to well below 2 °C above pre-industrial levels and pursuing efforts to limit the temperature increase to 1.5 °C' [44]. Achieving a 1.5 °C climate target is not yet a geophysical impossibility [45], but the stringent limits on GHG emission must be executed [46]. Previous researchers have studied how to improve energy efficiency to reduce energy costs and to reduce GHG emissions. Clean energy technology, renewable energy technologies, electric vehicle technology, building energy-efficient technology should be widely adopted in order to reduce GHG emissions [47]. Carbon dioxide removal technologies such as carbon capture and storage should be implemented [48–50]. Besides using modern technological means, a far-reaching transformation of the production pattern and lifestyle are required [51]. For example, many countries are developing a circular economy and establishing a circular society in order to achieve energy savings and reduce GHG emissions [52]; many cities are pursuing low-carbon practices to reduce GHG emissions [53].

Different sectors have different responses to climate changes [54]. Fung et al. [55] explored the relationships between sectoral energy consumption and temperature in Hong Kong using regression analysis. Ang [2] explored the relationships between sectoral energy consumption and temperature in Singapore and Hong Kong using regression analysis. All those two studies indicated that the impacts of climate warming would be the largest factor for the residential sector, followed by the commercial sector and the industrial sector. The results of this study show that TEC is more sensitive to climatic variables than REC in Guangzhou. The responses of REC to climate warming are different among Guangzhou and Hong Kong and Singapore. The reason is that REC is restricted by the wealth of society in Guangzhou. Therefore, people may use other energy-efficient equipment or wear fewer clothes on hot days rather than use air conditions since Guangzhou is not as rich as Hong Kong and Singapore. The different responses indicate that the effects of climate change on electricity consumption can be varied by income level. This conclusion can be verified by the results of the studies by Li et al. [56]. They concluded that households with differing levels of income will respond differently to the same temperature change in Shanghai.

With the socioeconomic development in Guangzhou, REC would be more sensitive to climate warming. The increase in REC due to climate warming could be larger than our predicted value in the future. In further studies, we have to study whether the wealth of society can influence the effect of climate change on electricity consumption. Further studies should focus on the international perspective rather than the issues of one city. Through further studies, we can quantify the impact of climate change on electricity consumption in different cities and then study what leads to different responses.

6. Conclusion

The effects of climate change on electricity consumption in Guangzhou were quantified. Firstly, the Mann-Kendall test method was used for estimating trends of historical and future climate changes. Secondly, regression models were developed for establishing the relationships among electricity consumption and climatic and socioeconomic features in Guangzhou. Finally, future electricity consumption in the 2030s, 2050s, and 2080s were predicted, where the future climatic and socioeconomic conditions were driven by four RCPs (13 CMIP5 climate models) and five SSPs.

The results indicate that there was a significant warming trend in Guangzhou during the period from 1971 to 2015; such warming trends will continue throughout the end of the 21st century under all RCPs. Both TEC and REC will increase with warming temperature. In addition, electricity consumption could vary significantly under different assumptions on the driving forces (e.g., climate warming and socioeconomic growth). As the radiative forcing grows, more electricity would be used for cooling in Guangzhou under RCP8.5 than other RCPs. Under RCP2.6, TEC and REC at the 2080s will be 161 and 44 TWh, respectively. Compared with RCP2.5, TEC and REC would increase by 11 and 1.04TWh under RCP8.5. Under four RCPs, the percentage changes of electricity consumption are ranging from 1.7% to 2.2% (in the 2030s), 3.1% to 6.1% (in the 2050s) and 3.2% to 10.4% (in the

2080s) for TEC. For REC the percentage changes are ranging from 0.6% to 0.8% (in the 2030s), 1.0% to 2.1% (in the 2050s) and 1.1% to 3.5% (in the 2080s). As for SSPs, if the world is characterized as fossil-fueled (SSP5), TEC by 2080s would be 204 TWh and REC would reach 58 TWh. However, if taking the green growth road (SSP1), TEC and REC would decrease by 37 and 14 TWh compared with that under SSP5.

Different sectors have different responses to the changes of socioeconomic and climate. In detail, REC is more sensitive to socioeconomic variables, while TEC is more sensitive to climatic variables. In the 2080s, TEC and REC are approximately seven times and fifteen times than that in the baseline period, respectively. In order to understand the impact of climate change on all sectors, more detailed results in all sectors are needed to be further investigated. On the other hand, this study mainly focuses on a single city, which could not fully represent the climatic and socioeconomic characterizes in other cities in China. Therefore, large-scale regions (e.g., China) are needed to be explored for further identifying climate change impacts on electricity consumption in different climate features.

CRediT authorship contribution statement

Shuguang Zheng: Conceptualization, Formal analysis, Methodology, Writing - original draft, Writing - review & editing. **Guohe Huang:** Conceptualization, Funding acquisition, Supervision. **Xiong Zhou:** Conceptualization, Methodology, Writing - review & editing. **Xiaohang Zhu:** Investigation, Data curation.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

This research was supported by the National Key Research and Development Plan of China (2016YFC0502800, 2016YFA0601502), the Natural Sciences Foundation of China (51520105013, 51679087), the 111 Program of China (B14008) and the Natural Science and Engineering Research Council of Canada.

Appendix

See Tables A1 and A2.

Table A1
Best subset regression analysis for total electricity consumption for the period from January 2004 to December 2012.

Models and variables	Coefficients	Sig.	VIF
Model 1 (Adj.R^2 = 0.958)			
Constant	11.0853	0.000	
ln GDP	0.6371	0.000	14.6
P	−0.0003	0.052	14.7
CDDs	0.0009	0.000	11.1
HDDs	0.0005	0.175	3.5
M_2	−0.1759	0.000	1.5
M_3	0.0792	0.001	1.7
M_6	0.0401	0.120	1.9
M_7	0.0995	0.001	2.5
M_8	0.1171	0.000	2.4
M_9	0.0860	0.001	1.9
M_{10}	0.0242	0.280	1.4
M_{11}	0.0589	0.014	1.6
M_{12}	0.1707	0.000	2.1
Model 2 (Adj.R^2 = 0.958)			
Constant	11.1048	0.000	
ln GDP	0.6304	0.000	14.4
P	−0.0003	0.069	14.4
CDDs	0.0009	0.000	10.5
HDDs	0.0005	0.175	3.5
M_2	−0.1777	0.000	1.5
M_3	0.0762	0.002	1.6
M_6	0.0297	0.214	1.6
M_7	0.0874	0.002	2.2
M_8	0.1051	0.000	2.1
M_9	0.0754	0.002	1.6
M_{11}	0.0540	0.022	1.5
M_{12}	0.1689	0.000	2.1
Model 3 (Adj.R^2 = 0.958)			
Constant	11.1021	0.000	
ln GDP	0.6368	0.000	14.6
P	−0.0003	0.050	14.7
CDDs	0.0008	0.000	21.5
HDDs	0.0004	0.300	4.0
M_2	−0.1761	0.000	1.5
M_3	0.0798	0.001	1.7
M_5	0.0238	0.479	3.2
M_6	0.0603	0.118	4.1
M_7	0.1242	0.008	6.0
M_8	0.1412	0.002	5.7

(*continued on next page*)

Table A1 (*continued*)

Models and variables	Coefficients	Sig.	VIF
M_9	0.1061	0.007	4.1
M_{10}	0.0384	0.203	2.5
M_{11}	0.0627	0.011	1.7
M_{12}	0.1671	0.000	2.2
Model 4 (Adj.R^2 = 0.958)			
Constant	11.0752	0.000	
ln GDP	0.6337	0.000	14.4
P	−0.0003	0.063	14.4
CDDs	0.0010	0.000	7.8
HDDs	0.0006	0.074	3.2
M_2	−0.1745	0.000	1.5
M_3	0.0801	0.001	1.6
M_7	0.0705	0.004	1.7
M_8	0.0888	0.000	1.6
M_9	0.0627	0.004	1.3
M_{11}	0.0557	0.018	1.5
M_{12}	0.1763	0.000	2.0
Model 5 (Adj.R^2 = 0.958)			
Constant	11.0895	0.000	
ln GDP	0.6419	0.000	14.8
P	−0.0003	0.037	15.3
CDDs	0.0007	0.001	37.1
HDDs	0.0005	0.219	4.3
M_2	−0.1610	0.000	2.4
M_3	0.1026	0.005	3.6
M_4	0.0429	0.390	7.0
M_5	0.0746	0.273	13.0
M_6	0.1158	0.125	15.9
M_7	0.1868	0.032	20.8
M_8	0.2030	0.018	20.2
M_9	0.1618	0.033	15.9
M_{11}	0.0852	0.032	5.2
M_{12}	0.0933	0.000	3.0
Model 6 (Adj.R^2 = 0.957)			
Constant	11.1980	0.000	
ln GDP	0.6171	0.000	14.0
P	−0.0002	0.120	14.0
CDDs	0.0009	0.000	2.8
M_2	−0.1992	0.000	1.4
M_3	0.0450	0.037	1.3
M_4	−0.0355	0.079	1.1
M_7	0.0803	0.001	1.5
M_8	0.0972	0.000	1.4
M_9	0.0622	0.005	1.3
M_{12}	0.1354	0.000	1.5
Model 7 (Adj.R^2 = 0.956)			
Constant	11.4705	0.000	
ln GDP	0.5359	0.000	2.8
CDDs	0.0009	0.000	1.4
M_2	−0.1963	0.000	1.3
M_3	0.0473	0.030	1.1
M_4	−0.0337	0.097	1.5
M_7	0.0804	0.001	1.4
M_8	0.0966	0.000	1.3
M_9	0.0608	0.006	1.5
M_{12}	0.1312	0.000	1.0
Model 8 (Adj.R^2 = 0.955)			
Constant	11.4629	0.000	
ln GDP	0.5360	0.000	1.0
CDDs	0.0009	0.000	2.8
M_2	−0.1899	0.000	1.3
M_3	0.0535	0.014	1.2
M_7	0.0851	0.000	1.4
M_8	0.1013	0.000	1.4
M_9	0.0658	0.003	1.3
M_{12}	0.1377	0.000	1.4

Table A2
Best subset regression analysis for residential electricity consumption for the period from January 2004 to December 2012.

Models and variables	Coefficients	Sig.	VIF
Model 1 (Adj.R^2 = 0.960)			
Constant	8.2336	0.000	
ln GDP	0.7964	0.000	14.5
P	−0.0002	0.297	14.6
M_4	0.0506	0.055	1.2
M_5	0.0678	0.011	1.2
M_6	0.1886	0.000	1.2
M_7	0.3969	0.000	1.2
M_8	0.5904	0.000	1.2
M_9	0.6676	0.000	1.3
M_{10}	0.5205	0.000	1.3
M_{11}	0.3385	0.000	1.3
M_{12}	0.0721	0.008	1.3
Model 2 (Adj.R^2 = 0.960)			
Constant	8.4664	0.000	
ln GDP	0.7277	0.000	1.0
M_4	0.0494	0.061	1.2
M_5	0.0660	0.013	1.2
M_6	0.1862	0.000	1.2
M_7	0.3939	0.000	1.2
M_8	0.5868	0.000	1.2
M_9	0.6635	0.000	1.2
M_{10}	0.5158	0.000	1.2
M_{11}	0.3331	0.000	1.2
M_{12}	0.0662	0.013	1.2
Model 3 (Adj.R^2 = 0.959)			
Constant	8.2485	0.000	
ln GDP	0.7973	0.000	14.5
P	−0.0002	0.278	14.8
CDDs	−0.0001	0.637	17.4
M_4	0.0648	0.107	2.8
M_5	0.0915	0.109	5.7
M_6	0.2154	0.001	7.0
M_7	0.4286	0.000	9.3
M_8	0.6216	0.000	9.0
M_9	0.6945	0.000	7.0
M_{10}	0.5414	0.000	4.7
M_{11}	0.3480	0.000	2.0
M_{12}	0.0713	0.009	1.3
Model 4 (Adj.R^2 = 0.958)			
Constant	8.3878	0.000	
ln GDP	0.7371	0.000	1.0
CDDs	0.0003	0.000	2.0
M_7	0.2583	0.000	1.5
M_8	0.4535	0.000	1.5
M_9	0.5461	0.000	1.3
M_{10}	0.4206	0.000	1.2
M_{11}	0.2798	0.000	1.0

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