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How will climate change affect the peak electricity load? Evidence from China

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ABSTRACT

The increasing peak load caused by climate change is challenging the electricity system reliability, and an accurate forecast of peak load can provide necessary support for the infrastructure investment and resilience enhancement. To support China's long-term power system planning, this study estimates the response functions of annual peak loads to maximum temperatures in China and then predicts the future peak loads under different scenarios. Key findings are summarized as follows: (1) There is a significantly positive correlation between the provincial highest temperatures and peak loads in China, and an increase of highest temperature by 1 °C will, on average, rise the peak load by 0.385 GW (2) The impacts of maximum temperature on the peak load vary substantially among different regions, and the impacts are the most significant in the Eastern China region. (3) The adoption and penetration of air conditioners is an important channel to materialize the impacts from temperature change to peak load. (4) The national peak load is forecasted to reach between 3807 GW and 6815 GW by the end of this century, which will require an additional infrastructure investment of 275–617 billion yuan per year.

1. Introduction

Secure electricity supply plays a vital role in supporting the healthy development of modern economy, but the increasing peak load driven by climate change is challenging the stable power system operation (De and Wing, 2019; Wang et al., 2020). Power outages occur more frequently during extreme weather, such as the large-scale electricity interruption in eastern provinces of China caused by the Liqima typhoon in 2019, the serious power outages in Zhengzhou city induced by heavy rain in 2021, the rolling blackouts in California caused by extreme heat in 2020 and the blackouts in Texas induced by extreme cold weather in 2021 (Pelley, 2021),[1] The impacts of climate change on the electricity demand can be analyzed from different time scales. In the short run, the frequency and intensity of cooling equipment (air conditioners, refrigerators, etc.) usages will increase in response to the temperature rise effects (Biardeau et al., 2019). In the long run, not only the utilization rate of cooling equipment will increase, but also the penetration rate of cooling equipment will rise (Bartos and Chester, 2015; Davis and Gertler, 2015). Most previous studies focused on investigating the impacts of climate change on the total amount of electricity consumption, but only a few studies took the lead in estimating the impacts of climate change on peak load (Fan et al., 2019; Zheng et al., 2019). However, a good knowledge of the peak load response functions will contribute greatly to a wiser power system planning and investment, which can also increase the resilience and reliability of electricity system (Burillo et al., 2017).

Quantifying the impacts of climate change on the peak load is complex work. On the one hand, accurate data of the daily or annual

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[1] The information of Liqima typhoon induced outages is drawn from https://baijiahao.baidu.com/s?id=1641753203187260784&wfr=spider&for=pc. The information of power outages in Zhengzhou city is obtained from http://k.sina.com.cn/article_1644729004_620892ac04000zk6x.html.The California blackouts data is drawn from a summary of restricted maintenance operations, alert, warning, emergency and flex alert notices issued from 1998 to present published by California Independent System Operator (ISO), see http://www.caiso.com/informed/Pages/Notifications/NoticeLog.aspx.

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peak load is not easily accessible, especially for the developing countries (Chaturvedi et al., 2014). This is also the major reason why the existing studies in this field are mainly concentrated in the United States (Franco and Sanstad, 2008) and some European countries (Giannakopoulos et al., 2016; Mirasgedis et al., 2007; Thornton et al., 2016). On the other hand, the peak load can be affected by various factors, such as climate change, income levels, population and urbanization rates, etc (Bartos and Chester, 2015). Selecting proper models, which comprehensively integrates all these factors, are key to accurately assess the impacts of climate change on peak load (Kuster et al., 2017).

China is the largest electricity consumer in the world, whose electricity consumption (7503 TWh) accounts for about 28% of the global total electricity consumption in 2019 (BP, 2020). At the same time, the national peak load in China has been growing rapidly in recent years, which reached 1003 GW in 2018. To meet this rising peak load, a large amount of money needs to be invested into the electricity supply infrastructure (generators, transmission and distribution lines, and transformers). The total investment into the electricity sector is 830 billion yuan in 2019, equaling to 0.84% of the same year GDP in China.[2] With a further increase of the peak load, additional investment will be caused to build new generators and transmission lines. To provide support for the long-term power system planning in China, this paper plans to estimate the impacts of climate change on the national peak load, aiming at answering the following three questions:

(1) How will the national peak load respond to the annual maximum temperature in China? What are the regional differences of these estimated responses?
(2) What are potential channels of climate change impacts on the peak load?
(3) How will the peak load in China evolve for the rest of this century?

The rest of this paper is organized as follows: Section 2 shows the literature review. Section 3 describes the methodology and data. Section 4 presents the empirical results and discussions. Section 5 summarizes the conclusions and proposes some policy recommendations.

2. Literature review

Analyzing the impacts of climate change on electricity consumption has become an increasing topic in the academic field. Based on the types of used methodologies, the existing studies can be classified into three categories, including econometric regression approach, artificial intelligence approach and engineering-based simulation approach.

Econometric regression approach is very popular in modeling the impacts of climate change on the electricity load. The popularly used models consist of linear regression models and non-linear regression models. Due to the simple calculation principle and strong explanatory capability, linear regression models are widely used in the load forecasting studies (Crowley and Joutz, 2020; Mirasgedis et al., 2007; Wang, 2018). The non-linear regression models use fitting methods to estimate the response functions of peak load to temperatures, such as semi-parametric regression (Gupta, 2012). Moreover, these models generally use temperature chambers to carry out segmented regression and add higher order terms of temperatures (Bartos et al., 2016; Davis and Gertler, 2015). Most of them have found an asymmetric U-shaped curve of load response functions to temperatures (Auffhammer et al., 2017). The 'right-side' load increase is caused by the cooling demand, while the 'left-side' rise is due to the heating demand (Wenz et al., 2017).

Artificial intelligence approach refers to the use of neural network models to simulate the influences of temperature changes on the electricity load. The advantage of this approach is that it can be used for non-linear forecasting, but it requires large amounts of data input from temperatures and other influencing factors. Behm et al. (2020) adopted the artificial neural network models to predict the load data of Germany and found that the peak load would reach 84 GW in 2025. He et al. (2015) combined neural network models and interval probability density method to quantify the probability of electricity density in China. Artificial intelligence approach has relatively higher accuracy when compared with other studies, but it is also criticized as a black box model and has weak interpretation ability.

Engineering-based simulation approach estimates the impacts of climate change on the electricity load by simulating the energy consumption of various end-use equipment in the buildings. The simulation approach can not only be used to simulate the peak load of a specific building, but it can also be employed to estimate the electricity load of all buildings within a region (Yao, 2020). As to the specific building load simulations, Ciancio et al. (2018) took climate factors into account and used EnergyPlus simulation program to forecast the hourly electricity demand of a single building. Dahanayake and Chow (2018) used the energy building simulation method to study the annual cooling load change for different buildings and scenarios in Hong Kong. As to the electricity simulations of all buildings at the regional level, Burillo et al. (2019) employed the simulation approach to analyze the peak load in Los Angeles, and found that the rising temperatures are expected to increase peak demand by 4–8% by 2060. Dirks et al. (2015) used Building Energy Demand Model (BEND) to estimate the peak load in Eastern grid in the United States, and found the peak load will increase by 18%–85% in all regions by the end of this century. Chaturvedi et al. (2014) combined the building energy consumption simulation with Global Change Assessment Model (GCAM) model to explore the long-term impact of climate change on power demand. However, this approach is more proper for modeling the electricity load in buildings, while it cannot be directly applied to estimate the total electricity load of a region or country.

As to the influencing factors considered in the estimations of climate change on electricity load, income, population, industrial structure and urbanization rate are the four frequently considered factors (Allen et al., 2016; Burillo et al., 2019; Willis, 2013). Miller et al. (2008) analyzed the impacts of income growth on the future peak power demand in California in the United States, and found that the income per capita will contribute to a significant increase in the future peak power demand. Mirasgedis et al. (2007) found that GDP has a significant positive impact on the power load in Greece. Chaturvedi et al. (2014) simulated the global future building energy demand, and found that the urbanization and industrial structure are the main driving factors of global energy use.

These previous studies can provide good support for our research, based on which we can estimate the impacts of climate change on the peak load in China. Compared with these previous studies, we contribute to the existing literature from the following two aspects. First, most studies focus on the impacts of climate change on the total electricity consumption, but our study is among the few studies which analyze the impacts of climate change on peak load. Understanding the influences of climate change on peak load is of great significance, which is helpful to formulate adaption and mitigation policies. On the one hand, compared with the total electricity consumption, peak load responds more sensitively to climate change (Auffhammer et al., 2017). On the other hand, peak load is an important basis for power system design and planning. In order to meet the peak demand, the "rule of thumb" of long-term infrastructure investment is to establish a capacity surplus of at least 15% of the peak load (Burillo et al., 2019). Second, most studies analyze the impacts of climate change factors and socio-economic factors on the future electricity load separately, while this study combines these two types of factors in the load projection by using the Shared Socio-economic Pathways (SSPs) and Representative

[2] The data is drawn from the list of basic data for electricity statistics in 2019 from China Electricity Council (CEC), see https://cec.org.cn/.

Concentration Pathways (RCPs).

3. Methodology

3.1. Response function model of peak load to temperatures

It is widely acknowledged that the response functions of electricity consumption to climate change exhibit asymmetric U-shaped curves (see Fig. 1), no matter for the total electricity consumption or the peak load (Auffhammer et al., 2017; Gupta, 2012; Mirasgedis et al., 2007; Wenz et al., 2017). For a specific region, the suitable temperature range locates between T_1 and T_2, indicating that there will not be any significant changes of peak load (P_0) within this range. However, the peak load will increase significantly when the temperature is either above T_2 or below T_1.

Although the impacts of climate change on electricity consumption are non-linear, this study will use a linear model to estimate the dose response function of peak load. There are two reasons for our choices. First, the relationship between temperature and peak load is linear at the range of extremely high temperatures. As seen from previous studies, non-linear econometric models are often used if the [T_1, T_2] is within the temperature ranges in their studies, such as the quadratic regression analysis models (Bartos et al., 2016; Huang et al., 2012; Wenz et al., 2017) and the piecewise linear fitting models (Auffhammer et al., 2017). However, linear models can also be used for estimating the response functions when the temperature is higher than T_2 (Wenz et al., 2017). Second, studies prefer to use non-linear econometric models for the hourly, daily and monthly temperature data, while they are more likely to use linear regression models for the annual temperature data (Davis and Gertler, 2015). Given the research targets and the data availability, we plan to use a two-way fixed effect panel data model to investigate the response functions of peak load to the changes of maximum temperature, see equation (1). [3]

$$PL_{it} = c + \beta T_{it} + \sum_{k=1}^{K} \gamma_k X_{kit} + \alpha_i + \theta_t + \varepsilon_{it} \tag{1}$$

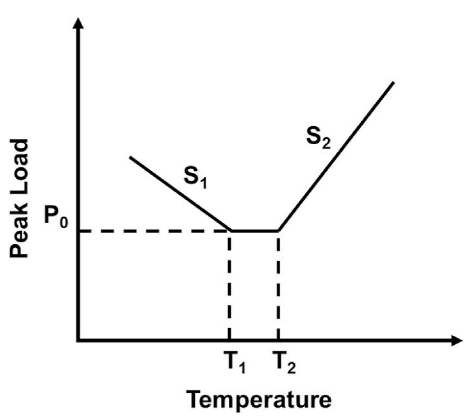

Fig. 1. Response function curve of peak loads to temperatures.

[3] There are two reasons why we only consider the maximum temperatures in the regression model. On the one hand, the annual peak load in most provinces of China occurs in summer rather than in winter. On the other hand, previous studies have found a linear relationship between maximum temperature and peak load and also only used maximum temperatures in estimating the peak load response functions (Wenz et al., 2017). Moreover, since the maximum temperature data in our study are all bigger than the comfortable temperature T_2 (24 °C) in China, so only the load-temperature responses in the part of 'S_2' in Fig. 1 is needed to be estimated.

Where i is the provincial index; t is the year index; k is the control variable index; PL_{it} is the peak load; T_{it} is the annual maximum temperature; X_{kit} represents the different control variables; α_i and θ_t represent the fixed effects of province and year respectively; ε_{it} is the disturbance term.

3.2. Data

This study employs a panel data of 31 provinces from 1998 to 2018 to estimate the response functions of peak loads to maximum temperatures.[4] The annual peak load of different provinces is selected as the dependent variable. The key independent variable maximum temperature selects the average value of the annual maximum temperature of all meteorological stations in the same province. Based on the suggestions from Waite et al. (2017), this study considers four control variables, which includes total population (Allen et al., 2016), provincial GDP (Mirasgedis et al., 2007), the proportion of the secondary industry and the urbanization rate (Chaturvedi et al., 2014). The data sources and explanations are shown in Table 1. The peak electricity load data is drawn from the power dispatch reports from China Electricity Council (CEC). The annual maximum temperature data is obtained from China Meteorological Administration (CMA). The provincial GDP data have been converted to the year of 1998 using the Consumer Price Index (CPI), and the CPI index is drawn from National Bureau of Statistics (NBS) of China. All the data of control variables are got from different statistical yearbooks published by the National Bureau of Statistics in China. The data in Table 1 are used as inputs of the regression model and are processed by Stata version 14.

To have a better understanding of the data used in this study, we have conducted a statistical analysis of the variables used in this study, see Table 2.

4. Results and discussions

4.1. The national response functions of peak load to climate change

A stepwise regression approach is adopted to estimate the regression model by introducing variables into the model one by one, see Table 3. We can see that all the estimated coefficients are consistent with our expectations, no matter for the variables we're interested in (annual maximum temperature) or for the other control variables. The R^2 of Model (4) is the highest (0.943) among all the four regression results, so it is used to illustrate the impacts of climate change on the peak load.

As seen from Table 3, the effects of maximum temperature on the

Table 1
Explanations and data sources of variables used in this study.

Variables	Explanations	Data sources
PL	Annual peak load	China Electricity Council
T	Annual maximum temperature	China Meteorological Data Service Centre
SR	Proportion of secondary industry	China Statistical Yearbook
UR	Urbanization rate	China Statistical Yearbook
GDP	Gross Domestic Product	China Statistical Yearbook
POP	Total population at the end of year	China Population Statistics Yearbook
AC	Total numbers of air conditioners	China statistical yearbook

[4] Due to the data availability problem, this study does not consider Hong Kong, Macao and Taiwan.

Table 2
Statistical description of variables.

Variable	Unit	Mean	Std. dev	Min	Max
PL	GW	16.49	16.84	0.04	100.40
T	°C	35.73	3.14	24.78	40.95
SR	%	45.26	8.29	18.63	61.48
UR	%	48.33	16.27	18.56	89.60
GDP	Trillion yuan	1.00	1.08	0.01	7.04
POP	Million persons	42.47	26.98	2.52	113.50

Notes: The data of GDP in this table are expressed in the 1998 prices.

Table 3
National regression results of load-temperature responses.

Variables	(1)	(2)	(3)	(4)
	PL	PL	PL	PL
T	0.456***	0.455**	0.497**	0.385***
	(3.022)	(2.633)	(2.582)	(3.171)
POP	1.960***	2.137***	2.012***	0.415**
	(7.358)	(8.861)	(10.218)	(2.256)
UR		0.861***	1.000***	0.370***
		(2.896)	(3.185)	(3.408)
SR			−0.309*	−0.178**
			(-1.912)	(-2.215)
GDP				12.233***
				(10.528)
Constant	−88.986***	−127.514***	−115.771***	−34.183***
	(-6.888)	(-6.329)	(-7.340)	(-3.346)
Observations	651	651	651	651
R-squared	0.761	0.804	0.814	0.943
Number of id	31	31	31	31
Province FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES

Robust t-statistics in parentheses, ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

peak load are positive at the 1% significance level. In particular, a 1 °C increase in the maximum temperature will increase the peak load by an average of 0.385 GW. This result also indicates that the temperature rise of 1 °C will increase the peak load by 2.33% compared with the historical average level. [5] Similar to the previous studies, the influence of temperature on peak load is greater than that of the total electricity consumption (Auffhammer et al., 2017). Taken the Guangzhou city as an example, the residential electricity consumption will increase by 0.9% for 1 °C of temperature rise (Zheng et al., 2019). Moreover, we have also compared our results with those from other countries or regions, see Table 4. We can see that our estimation result are very close to the results in Los Angeles (0.39 GW/°C) and are slightly higher than 0.27 GW/°C in Phoenix (Burillo et al., 2017), which can prove the robustness of our results at a certain extent.

Table 4
The responses of peak load to maximum temperature changes in different studies.

Study	region	period	methods	results
Burillo et al. (2017)	Los Angeles, USA	2015–2016	Spatial error model	0.39 GW/°C
Burillo et al. (2017)	Phoenix, USA	2015–2016	Spatial error model	0.27 GW/°C
Wenz et al. (2017)	Spain	2006–2012	Piecewise OLS model	0.44 GW/°C
This study	China	1998–2018	Two-way FE model	0.38 GW/°C

As for the control variables, the directions of estimated coefficients are also consistent with those in previous studies. All the estimated coefficients of *POP*、*UR*、*GDP* are positive and statistically significant, indicating that the increase of population, urbanization rate and economic output levels will all result in higher levels of peak load. This is because the increase of regional economic growth (Chaturvedi et al., 2014), the rise of urbanization rate (Mirasgedis et al., 2007) and expansion of population (Allen et al., 2016) will all push up the regional power load (Waite et al., 2017). The peak load is also significantly negatively related to economic shares of the provincial secondary industry. Previous studies have found that industrial structure will have an impact on power load demand, and the proportion of the secondary industry is negatively correlated with the peak load (Waite et al., 2017). The power load can be divided into two parts, which include the base load and the peak load. The base load is mainly composed of electricity consumption from heavy industry and light industry, while the change of peak load depends on the electricity consumption from the tertiary sector and residential sector. Therefore, The reduction of the output share of the secondary industry will increase the share of the tertiary industry, thus leading to the increase of peak load (Wang et al., 2020).

Economic development can stimulate the growth of electricity consumption, while the economic development also relies greatly on the energy consumption. If there are endogenous problems with *GDP*, the estimated parameter will be biased and inconsistent. To test the existence of this endogeneity problem, we followed the suggestions from Reed and Robert (2015) and take the first-order lag term of *GDP* as an instrumental variable (IV), and then use a Two-Stage Least Square (TSLS) estimation method. The results are shown in Table 5. As can be seen from the regression results comparison between model (1) and model (2), we can see that the estimated two coefficients of *GDP* are the same, no matter whether the fixed effects of time are controlled or not. Moreover, the estimated coefficients of maximum temperature are also very close to the result of Model 4 in Table 3, indicating the robustness of our estimation results. All these results support the non-existence of the endogenous effect. This is also consistent with the conclusions from Jamaaluddin et al. (2019), who stated that peak load only lasts for a very short time and cannot significantly affect the explanatory variables as annual electricity consumption does.

4.2. The regional differences of the load-temperature responses

As pointed out by Waite et al. (2017), the regional heterogeneity can affect the responses of electricity load to temperature changes. The electricity load in economically developed countries and regions tends

Table 5
Robustness test results by using IV instrumental variables.

Variables	(1)	(2)
	PL	PL
GDP	12.606***	12.606***
	(26.093)	(27.229)
T	0.341***	0.437***
	(3.130)	(3.693)
Constant	−30.374***	−51.680***
	(-6.149)	(-8.565)
Observations	620	620
R-squared	0.973	0.975
Province FE	YES	YES
Year FE	NO	YES
Control Variable	YES	YES

Robust z-statistics in parentheses, ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

[5] This data is compared to the historical average value of the peak power load from 1998 to 2018.

to have larger responses to the temperature changes than that in the poor regions. With the introduction of the reform and opening-up policy in 1978, there are big economic development gaps between the eastern coastal provinces and inland provinces (central region and west region).[6] To analyze the regional differences of the climate change impacts on peak load, we have estimated the load-temperature responses for the three regions in China individually, see Table 6. [7]

As can be seen from Table 6, there are significant differences in the impacts of climate change on the peak load in different regions. In the Eastern China Region, characterized by higher economic levels, a 1 °C rise in the maximum temperature will significantly result in a 0.708 GW increase in the peak load. However, the amount of the climate change impacts will rapidly be reduced to 0.116 GW in the less developed Central China Region, and the impacts also become insignificant. As for the economically underdeveloped Western China Region, the maximum temperature is found to have little effect on the peak load. The differences in the impacts of temperature rise on peak load among regions can be partly explained by the different economic development levels among regions. On the one hand, the air conditioning ownership in the economically developed eastern China region is higher than that in the economically underdeveloped central and western China regions. In 2018, the air conditioning ownership per capita in the eastern China region is 1.67 times that in the central China region and 2.78 times that in the western China region. On the other hand, the disposable income per capita in the eastern China region is higher. In 2018, the disposable income per capita in the eastern China region is 1.62 times that of the central China region and 1.70 times that of the western China region. The higher disposable income allows residents to bear a higher electricity charge level, so the utilization rate of air conditioning will be higher than that in the central and western China regions (Rivers and Shaffer, 2020). Therefore, more attention should be paid to the economic developed regions in coping with the peak load impacts from climate change.

Table 6
Regional differences of the peak load-temperature responses.

Variables	(1) Eastern China region	(2) Central China region	(3) Western China region
T	0.708***	0.116	−0.001
	(4.455)	(0.668)	(-0.008)
POP	0.399**	−0.565	0.345
	(2.644)	(-1.297)	(0.636)
UR	0.431*	0.703***	−0.064
	(2.052)	(4.254)	(-0.221)
SR	−0.242	−0.198	−0.282**
	(-1.180)	(-1.671)	(-2.626)
GDP	13.201***	10.661**	8.790***
	(10.839)	(2.580)	(6.012)
Constant	−51.033***	11.791	4.415
	(-3.600)	(0.611)	(0.331)
Observations	252	189	210
R-squared	0.968	0.924	0.896
Number of id	12	9	10
Province FE	YES	YES	YES
Year FE	YES	YES	YES

Robust t-statistics in parentheses, ***p < 0.01, **p < 0.05, *p < 0.1.

4.3. *The channels from temperature changes to peak load variations*

The development of air conditioning has increased the intensity and frequency of peak load events, which will lead to significant investment in power generation and transmission infrastructure (Biardeau et al., 2019; Davis and Gertler, 2015). China is the biggest owner of air conditioners in the world, whose domestic sales account for 66% of the world in 2018 (SIC, 2018). Previous studies have shown that the influence of temperature on the peak load is likely to be realized through the usages of air conditioning. Biardeau et al. (2019) found that the temperature rise will increase the use of air conditioning, which will push up peak load demand. In an empirical study of Mexico, Davis and Gertler (2015) found that the temperature-load response function was significantly steeper for the households living in states with higher air conditioning penetration levels. Following the approach of Baron and Kenny (1999), this study analyzes the mediating effects of the total number of air conditioners in the load-temperature responses, see equations (2)–(4).

$$PL_{it} = \mathrm{b}_0 + b_1 T_{it} + \sum_{k=1}^{K} b_{2k} X_{kit} + \alpha_i + \theta_t + \varepsilon_{it} \tag{2}$$

$$AC_{it} = b_0 + b_1 T_{it} + \sum_{k=1}^{K} b_{2k} X_{kit} + \alpha_i + \theta_t + \varepsilon_{it} \tag{3}$$

$$PL_{it} = b_0 + b_1 T_{it} + b_2 AC_{it} + \sum_{k=1}^{K} b_{3k} X_{kit} + \alpha_i + \theta_t + \varepsilon_{it} \tag{4}$$

Where AC_{it} represents the total number of air conditioners in province i in year t. The other variable definitions are shown in Table 1.

The regression results of the mediating effects analysis are shown in Table 7. Model (1) presents the business-as-usual results used for comparison. Model (2) shows the impacts of maximum temperatures on the total number of air conditioners, while Model (3) presents the influences of both maximum temperatures and air conditioner quantity on the peak loads. As seen from the results of Model (2), the maximum temperature

Table 7
The mediating effects of air conditioners on the load-temperature responses.

Variables	(1) PL	(2) AC	(3) PL
T	0.385***	0.248***	0.269**
	(3.171)	(2.864)	(2.344)
AC			0.467***
			(3.760)
Constant	−34.183***	−28.932***	−20.658*
	(-3.346)	(-3.562)	(-1.987)
Observations	651	651	651
R-squared	0.943	0.902	0.950
Province FE	YES	YES	YES
Year FE	YES	YES	YES
Control Variable	YES	YES	YES

Notes: Robust t-statistics in parentheses, ***p < 0.01, **p < 0.05, *p < 0.1.

[6] In 2018, the GDP per capita of the three regions was 56300 yuan (Eastern China region), 34800 yuan (Central China region) and 33200 yuan (Western China region) respectively.

[7] According to the National Development and Reform Commission (NDRC) in China, China is divided into eastern region, central region and western region according to the geographical locations. The Eastern China region has 12 provinces, autonomous regions and municipalities, including Beijing, Tianjin, Hebei, Liaoning, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, Guangxi and Hainan. The Central China region has nine provinces and autonomous regions, namely Shanxi, Inner Mongolia, Jilin, Heilongjiang, Anhui, Jiangxi, Henan, Hubei and Hunan. The Western China region comprises nine provinces and autonomous regions, including Sichuan, Guizhou, Yunnan, Tibet, Shaanxi, Gansu, Ningxia, Qinghai and Xinjiang.

has a significantly positive impact on the total number of installed air conditioners. Comparing the results of Model (1) with that from Model (3), we can see that the impacts of maximum temperatures will reduce from 0.385 GW/°C to 0.269 GW/°C if the total number of air conditioners is added to the regression model. Moreover, the significance level of the estimated coefficients also decreases from 1% to 5%. Combining the estimated results of these three models, we can say that the number of air conditioners is an important channel to materialize the impacts from temperature change to peak load. This is also consistent with the conclusions of Sieber (2013), who have found that extreme hot weather events themselves will also contribute to the increase of peak load. Forzieri et al. (2018) also found that extreme weather events, such as heat wave and drought, will have a significant impact on peak load.

4.4. The projections of future peak load and required infrastructure investment

In this section, the estimated load-temperature response functions are employed to forecast the peak load and the required infrastructure investment in the future. Four scenarios are developed based on the SSPs from the sixth international coupling mode comparison plan (CMIP6) and the RCPs from Vuuren et al. (2011), see Table 8. Four combined SSP-RCP scenarios are developed based on the data availability. All the data of input variables are drawn from previous studies, including the maximum temperature (Chen et al., 2021), population (Huang et al., 2019), urbanization rate (Jing et al., 2020), the economic share of secondary industry and GDP (Jiang et al., 2017).

Using the estimated temperature-load response functions, we first analyze how the national peak load will change in the rest of 21st century, see Fig. 2. We can see that the national peak load is the highest (6816 GW) under the SSP 5-RCP 8.5 scenario by the end of this century, while it is the lowest (3808 GW) under the SSP4-RCP 6.0 scenario. Moreover, the socioeconomic variables are found to have larger impacts on the peak load than the temperatures, this can be evidenced by the fact that the peak load under SSP1-RCP 2.6 is higher than that under SSP4-RCP 6.0. The increased peak load from climate change will cause additional investment demand for electricity supply infrastructure, the amount of which will rely on the technology choices greatly. Although it is difficult to predict the accurate share of different technologies due to the significant uncertainties, the wind generators and solar generators are expected to be deployed at a large scale in the future to meet the Carbon Neutrality Target set by the Chinese government. Therefore, this study only considers these two technologies in estimating the needed infrastructure investment. To meet the projected peak load demand, the annual investment will range from 298 to 617 billion yuan for the wind generators, and from 275 to 570 billion yuan for the solar generators. [8] The wide range of the estimated investment cost indicates that different climate change mitigation policies and socio-economic development paths will have a significant impact on the infrastructure investment.

This study has also forecasted the annual peak load when only the impacts of temperature changes are considered, see Fig. 3. We can see that the average increase in the peak load is about 399 GW under the four RCPs by the end of this century. The trajectory of RCP 8.5 will generally have the highest increase of peak load, while the path of RCP 2.6 will have the smallest rise. The peak load shows a significant positive relationship with the temperature increase under different RCPs. This also indicates that more effective climate change mitigation policies would significantly reduce the impacts of temperature on peak load.

Furthermore, we have compared our estimation results with that from previous studies, see Table 9. We can see that our estimation results are much bigger than that of other countries. This is because most previous studies usually only consider the increase of peak load caused by the temperature changes, while this study considers both the changes of climate variables and socioeconomic variables. This can also be supported by the results from China. The growth rate of China's peak load is between 37% and 41% when only the climate change variables are considered, while the growth rate will be 280%–580% if both two types of variables are modeled. This shows that the growth rate of China's peak load depends largely on the level of economic and social development.

In addition, we have also investigated the regional differences of the peak load projections under different scenarios, see Fig. 4. To save space, only the years of 2030, 2050 and 2100 are shown in this figure. From the perspective of the spatial distributions of the peak loads, we can see that the provinces with relatively higher peak loads are mostly located in the Eastern China Region, followed by the loads of provinces in the Central China Region. The peak loads in the Western China Region are the lowest. Moreover, these conclusions are consistent no matter which scenario is selected.

5. Conclusions and policy implications

5.1. Conclusions

With the increasing electrification rate, electricity consumption is becoming more sensitive to the temperature variations from climate change. Peak load is a key input parameter for the power system planning, and a biased prediction can result in serious electricity outage events. To provide necessary guidance for the peak load projection in the future, this study first employs a fixed-effects panel data model to estimate the response functions of peak load to temperature changes from 1998 to 2018. Then, the heterogeneity of load-temperature responses is investigated for regions with different income levels. After that, the mediating effects of air conditioner penetrations are tested for the responses of peak load to climate change. Finally, the peak load and required infrastructure investment in the future are forecasted under different scenarios. During this process, we have obtained the following major conclusions.

(1) The annual maximum temperature is found to have significant positive impacts on the provincial peak load in China. A 1 °C increase in the maximum temperature will increase the peak load by an average of 0.385 GW. Moreover, significant heterogeneity exists among different regions with different income levels. For example, every 1 °C increase of the maximum temperature will lead to an increase of 0.708 GW of peak load in the rich Eastern China Region, while impacts will be reduced to 0.116 GW in the less developed Central China Region.
(2) Air conditioner penetrations are tested to have significant mediating effects to materialize the impacts from climate change to peak load. The annual maximum temperature rises by 1 °C will increase the total provincial ownerships of air conditioners by 0.248 million, and 1 million increases of the total number of air conditioners will raise the peak load by 0.467 GW. Moreover, if the mediating effects of air conditioning are eliminated, the intensity and significance of the temperature effects on peak load will be greatly reduced.
(3) China's national peak load is forecasted to increase substantially at the end of this century, and an additional investment of 275–617 billion yuan per year will be needed to ensure a reliable

[8] The cost projection of wind power generation projects and photovoltaic power generation projects are based on the China Electric Power Technology and Economy Development Research Report 2019, and the operating reserve share of installed capacity is set as 15% based on Chen et al. (2021).

Table 8
Explanations of different scenarios use in the load projection.

Scenario name	SSP1-RCP 2.6	SSP2-RCP 4.5	SSP4-RCP 6.0	SSP5-RCP 8.5
Radiative forcing	2.6 $W{\cdot}m^{-2}$	4.5 $W{\cdot}m^{-2}$	6.0 $W{\cdot}m^{-2}$	8.5 $W{\cdot}m^{-2}$
Population growth	Moderate growth followed by decline	Moderate growth followed by decline	High-speed growth	Moderate growth followed by decline
Urbanization	All regions are rapidly urbanized	All regions are Moderate urbanized	Low-and middle-income are rapidly urbanized	All regions are rapidly urbanized
Total factor productivity	Moderate growth, high-speed convergence	Moderate growth, moderate convergence	Moderate growth, low convergence	High growth, high convergence
Economic development	High-speed growth	Medium growth	Medium growth	High-speed growth

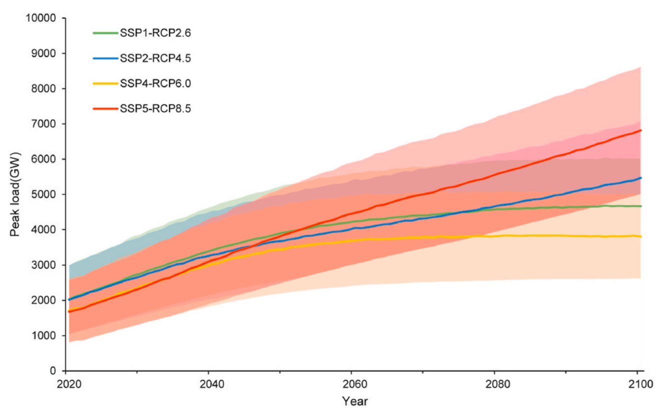

Fig. 2. The projected national peak load of China under different scenarios.

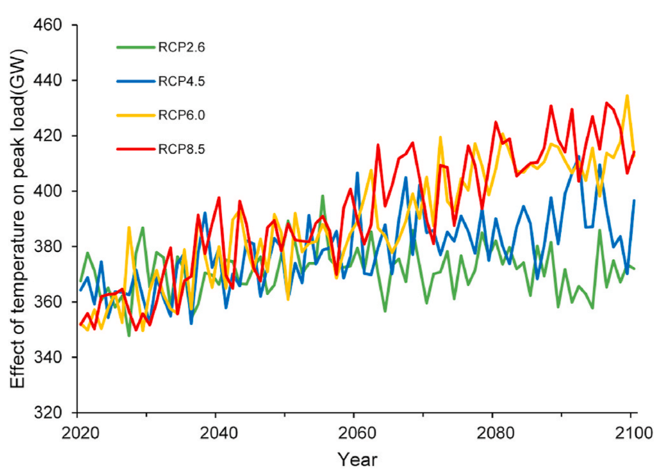

Fig. 3. The prediction of the temperature impacts on peak load under different RCPs.

supply. Using the estimated load-temperature response functions, the national peak load is expected to reach between 3807 GW and 6815 GW in 2100 under different climate and socio-economic scenarios. Moreover, the impacts of temperature rise can only contribute to 20% of the peak load increase, while the majority of load increase is affected by the changes of socioeconomic factors in China. In addition, the spatial distributions of the load will remain the same with the current status, and the Eastern China Region will still have the highest peak load.

5.2. Policy implications

Based on the above conclusions, this paper proposes the following policy implications.

First, since the climate change has significant impacts on the peak load demand and the implementation of different mitigation policies will also change its pathways, it is necessary for the power system planners to integrate the climate change and relevant policies into the long-term plan. For example, a dynamic revision mechanism can be established to integrate the impacts of climate change to the power system planning.

Second, the increasing penetration and usage of air conditioners are found to be a significant channel for the peak load to respond to climate changes. Moreover, the load from air conditioners can account for as large as 50% of the peak load during hot summers,[9] posing great challenges to the safe power system operation. Therefore, it is necessary to promote technological progress to improve the efficiencies of air conditioners, such as enhancing the house insulation, using cold roofs and deploying passive cooling systems (Biardeau et al., 2019). In addition, it is also important to develop wise demand response programs to guide the consumer behavior so as to reduce the peak load.

Third, it is good to take advantage of the electricity market to guide the optimal investment and plan in response to the climate changes. Electricity market can provide good signals of how different consumers should respond to the changes of climate and prices. Moreover, the signals from electricity market can motivate better resource allocation with consideration of the provincial differences regarding the climate change and load responses, thus achieving larger levels of social welfare.

Although this study has answered several important questions related to the responses of peak load to climate change in China, there are still several issues to be addressed in further studies. The pathways of future peak load demand can be affected by the important climate change policies, so it is necessary to dynamically change and revise the forecasting results when shocks of new policies appear. Moreover, data with smaller spatial granularity can be used to forecast the future peak load more accurately, such as the city level data and county level data. Last, the accuracy of the estimated results may be affected by the existence of endogeneity problem (missing variables), which can be further improved in the future. All these improvements can contribute to a better understanding of impacts of climate change on the peak load.

CRediT authorship contribution statement

Hao Chen: Conceptualization, Methodology, Writing – original draft. **Haobo Yan:** Software, Data curation, Visualization. **Kai Gong:** Software, Data curation, Visualization. **Xiao-Chen Yuan:** Software, Data curation, Writing – review & editing.

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.

[9] The data is drawn from http://www.bj.sgcc.com.cn/.

Table 9
The comparison of peak load forecasts among different studies.

Study	Period	Region	Peak load growth rate under different paths			
			SSP1-RCP2.6	SSP2-RCP4.5	SSP4-RCP6.0	SSP5-RCP8.5
Auffhammer et al. (2017)	2014–2100	United States	—	4%	—	10%
Bartos et al. (2016)	1990–2100	United States	6%	10%	—	24%
Burillo et al. (2017)	2016–2100	Phoenix/Los Angeles	—	6%/7%	—	28%/23%
Wenz et al. (2017)	2012–2099	Southern and Western Europe/Northern Europe	1%/-3%	2%/-4%	—	5%/-6%
This study (climate variables included)	2018–2100	China	37%	40%	41%	41%
This study (Climate and socioeconomic variables included)	2018–2100	China	365%	445%	280%	580%

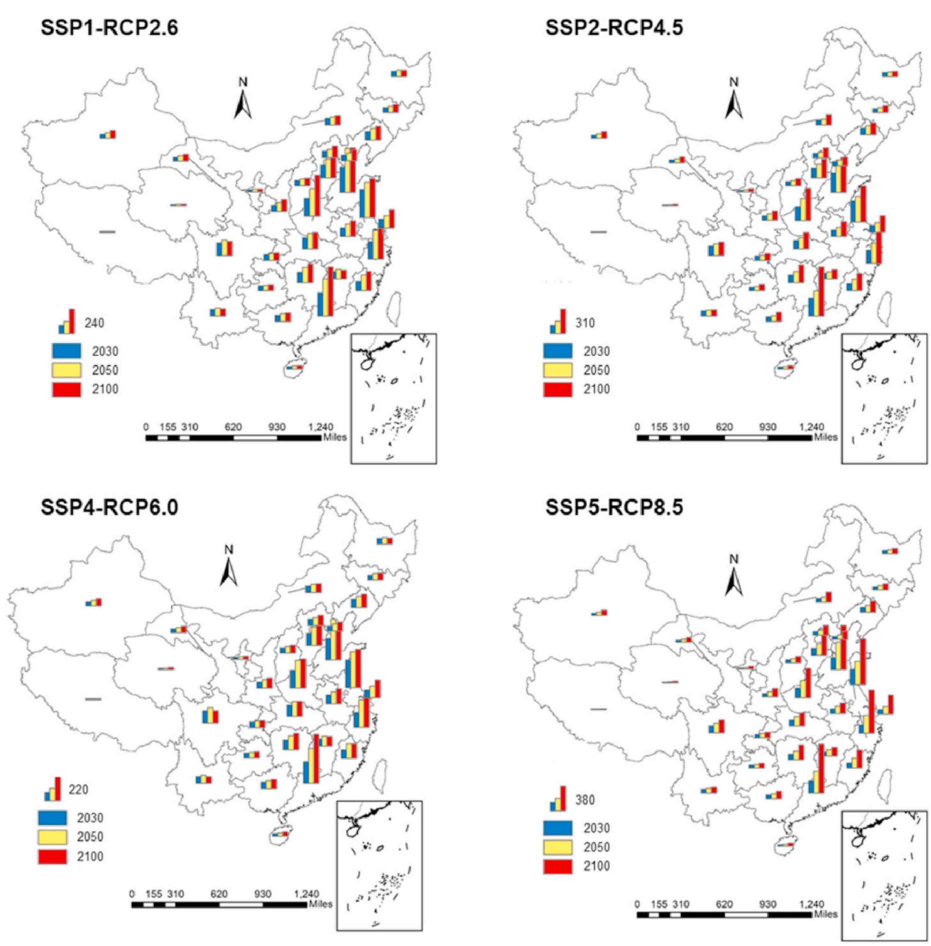

Fig. 4. The forecast of provincial peak loads in 2030, 2050 and 2100.

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