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Fighting climate change together: The regional heterogenous impacts of climate change and potentials of regional power market

Feng Song [a], Xintong Miao [a], Fang Xia [b,c,*]

[a] School of Applied Economics, Renmin University of China, China
[b] College of Economics and Management, China Agricultural University, China
[c] Academy of Global Food Economics and Policy, China Agricultural University, China

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ABSTRACT

This study measures the impact of the climate change on China's electricity sector and how the heterogenous impact across a large geographic area could be employed to better adapt to climate change. A unique dataset of daily load in China's five southern provinces in 2018 is employed to estimate the temperature response functions and predict the future changes driven by climate change. The results show that although the rising temperature will normalize the higher level of electricity demand on average, it exerts a heterogeneous impact on the electricity demand of different provinces, thereby creating opportunities for trade and cooperation among these five provinces. By using a cost-minimization model, we find that reforming the electricity sector through economic dispatch and expanding the dispatch area can serve as a cost-effective "soft" approach to adapting to climate change.

1. Introduction

To cope with the climate change, the electricity sector is anticipated to play an important role in both mitigation and adaption. On the one hand, the electricity sector accounts for nearly 40 % of global carbon emissions (International Energy Agency, 2024). To meet the long-term mitigation target agreed upon at 1.5 °C, it must undergo a fundamental transition towards to zero-carbon or low-carbon generation sources. On the other hand, the electricity sector itself is vulnerable to climate change, as extreme weather can significantly change demand patterns and interrupt the electricity supply chain from generation to transmission to distribution (ADB, 2012; IPCC, 2022). Assisting the electricity sector in adapting to climate change not only mitigates its susceptibility to climate-related risks but also fosters the development of a sustainable energy future.

To better adapt to climate change in the electricity sector, it is essential to understand how climate change affects both inter-day and intraday electricity demand. This understanding is crucial because operation safety and capacity adequacy planning in the electricity sector rely heavily on granular load data. Previous work on the relationship between climate change and electricity demand at regional or country level primarily focuses on developed countries, such as the United States (Franco and Sanstad, 2008; Miller et al., 2008; Auffhammer and Aroonruengsawat, 2011; Jaglom et al., 2014; Coffey et al., 2015) and European Countries (Abrell and Rausch., 2016; Wenz et al., 2017). However, current forecasts suggest that most of the growth in electricity demand will come from the developing world (Wolfram et al., 2012; Auffhammer and Wolfram, 2014; Davis and Gertler, 2015). The limited research on developing regions is likely due to the lack of high-resolution temporal and geographic data needed for accurate estimation of temperature-response functions in electricity demand. Recent studies on China have begun to address this gap, though most have focused on the residential sector (Cao et al., 2019; Zhang et al., 2022; Zhang et al., 2023; Nie et al., 2024).

Our study intends to fill the literature gap by measuring the impact of the climate change on China's electricity sector and how the heterogenous impact across a large geographic area could be employed to better adapt to climate change. China is currently the largest producer and consumer of electricity, as well as the largest carbon emitter, accounting 31 % of world's emissions in 2022 (Friedlingstein et al., 2023). It also suffers from the impacts of climate change, which include warmer average temperatures and more "extreme" weather events.

Building on previous studies (Auffhammer et al., 2017; Wenz et al., 2017; Li et al., 2019; Zhang et al., 2022), we first analyze the effects of

* Corresponding author at: College of Economics and Management, China Agricultural University, No. 17 Qinghua Donglu, Haidian District, Beijing 100083, China.
E-mail addresses: songfeng@ruc.edu.cn (F. Song), xintongmiao@ruc.edu.cn (X. Miao), xiafang@cau.edu.cn (F. Xia).

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climate change on electricity demand patterns in five provinces in Southern China. For empirical estimation, we have aggregated the high-frequency time series data to a daily frequency to estimate separate response functions and predictions for both average and peak loads for each province at the end of the century. This information is used to simulate how climate change impacts the intensity of peak-load events and overall electricity consumption under different climate change scenarios (RCP4.5 and RCP8.5). Climate change has led to varied impacts across different provinces, influencing their demand patterns and altering the inter-provincial trade dynamics. The results suggest the possibility of enlarging the regional dispatch area to better adapt to climate change. A partial market equilibrium model is constructed to simulate the potential benefits of expanding the dispatch area. By assuming system operators implement economic dispatch to minimize total operating costs, we simulate the Southern Grid's operation on a daily basis across the five provinces under various climate scenarios.

The findings can be summarized as following. First, the temperature-response functions of all five provinces exhibit U-shaped curves, which is consistent with previous literature. However, these curves are asymmetrical due to diverse climatic conditions across the provinces. Hot provinces, including Guangdong and Guangxi, exhibit relatively complete U-curves, while the extremely hot province (Hainan) displays only the right half. In contrast, the relatively cool provinces (Guizhou and Yunnan) show only the left half.

Second, future end-of-century predictions (RCP4.5 and RCP8.5 scenarios) suggest that climate change will lead to a consistently higher level of electricity demand. The average load is expected to respond more strongly to temperature increases than the peak load. Individual provincial results show heterogeneous impacts of climate change: the electricity demand in three "hot" provinces (Guangdong, Guangxi, and Hainan) is positively affected, while two "cool" provinces (Yunnan and Guizhou) are negatively affected. This alters the demand correlations among these provinces with temperature changes, consequently impacting inter-provincial trade patterns. These changes will affect investment plans for future infrastructure construction and guide the direction of electricity market reforms.

Third, we find that reforming the electricity sector through economic dispatch and expanding the dispatch area serves as a cost-effective "soft" approach to adapting to climate change. Under the current planning-based mechanism, the existing installed capacity cannot meet power demand under the RCP4.5 and RCP8.5 scenarios. However, by expanding the dispatch area among these five provinces, the installed capacity and transmission infrastructure in place as of 2018 can accommodate the loads projected under different climate scenarios. Based on our computations, expanding the dispatch area across five provinces could yield a minimum saving of $4547 million in capacity investments, thereby facilitating cost-effective adaptation of the electricity sector to climate change.

We make two contributions to the existing literature. First, this is the first study to use data with better temporal and geographical granularity to estimate the temperature-electricity response function for a substantial part of China's territory. While most studies have focused on developed countries (e.g., Auffhammer et al., 2017; Wenz et al., 2017 on 35 European countries), few have quantified the impact of climate change on China's electricity sector. Li et al. (2019) is the first quantitative study of China's electricity sector, using daily household-level electricity consumption in Shanghai to estimate the temperature-response function for residential electricity consumption. Unlike Li et al. (2019), which focuses solely on residential demand at the city level, our dataset covers all sectoral electricity demand across a much larger geographic area. This detailed, daily-frequency grid-level data provides substantial regional variations and allows for a deeper understanding of how electricity demand responds to climate change.

Second, we bridge the literature on climate change and the deregulation of electricity markets. Our study considers the demand correlation among provinces and the possibility of reforming the electricity sector through economic dispatch and enlarging the dispatch area (Lin et al., 2022), providing a more cost-effective "soft" approach to adapting to climate change. The changing spatial and temporal patterns of consumption and peak load often require planning for new electricity generation capacity, transmission lines, and storage capacity (Abrell and Rausch, 2016). While expanding transmission capacity and investing in energy storage can alleviate grid flexibility issues, these solutions are often prohibitively expensive. Alternatively, market innovations may be less costly. Compared to "hard" investments in energy storage and electricity transmission infrastructure, market reforms can be seen as more "soft" arrangements, which might be more cost-effective for developing countries.

The remainder of this paper proceeds as follows. Section 2 introduces the studying area and our dataset. Section 3 presents the identification strategy and estimation results. In Section 4, we use the estimation results to predict future demand and calculate the cross-province demand correlations to evaluate the potential for reform. Section 5 explores the necessity and benefits of building up a regional market among the studying area. Section 6 concludes the paper.

2. Background and data

This study compiles a unique dataset containing detailed hourly data on electricity demand, production, and inter-provincial electricity exchange trade in China's southern grid covering area for the year 2018. Our data are collected from various sources.

Electricity data. The installed capacity and the transmission line capacities are collected from the 2018 Annual Dispatch Report of Southern Power Grid. The hourly data of provincial electricity demand are obtained from the South China Energy Regulatory Office of the National Energy Administration.

Climate data. We obtain temperature and precipitation data for 2018 from the China Meteorological Data Service Centre. The dataset covers continuous daily weather records from 699 monitoring stations in 31 provinces, including 115 monitoring stations in the five provinces we studied.

Table 1 gives a summary statistic of the China southern grid, which covers five provinces, Guangdong, Guangxi, Yunnan, Guizhou, and Hainan. Primary analysis reveals some interesting facts. First, this region provides electricity service for 248 million or 19.2 % of Chinese population. In 2018, the aggregate electricity usage amounted to approximately 1163 TWh, representing 17 % of China's total electricity consumption – a figure comparable to Russia's total consumption and surpassing the combined consumption of Central and Southern America. The overall installed capacity within this region reached 304GW in the year 2018.

Second, while all five provinces lie in the southern part of China, their individual climates can vary significantly. Guangdong and Guangxi both have humid subtropical climates with warm, humid summers and milder winters. Hainan has a tropical monsoon climate with hot, humid summers and vulnerability to typhoons. These three provinces can be categorized as "hot" provinces. Guizhou and Yunnan are situated on the

Table 1
Summary statistics of the study region.

	Guangdong	Guangxi	Guizhou	Yunnan	Hainan
Max load (MWh)	83,103	18,187	16,702	18,588	3941
Mean load (MWh)	70,609	15,164	13,893	15,969	3235
Average Temperature (°C)	22.36	21.11	24.50	16.43	24.51
Average Humidity	79.53	79.56	82.13	73.28	82.13
GDP (billion US dollars)	1414.50	296.01	215.35	260.07	70.28
Population (million)	113.46	49.26	36.00	48.30	9.34
Installed capacity (GW)	112.82	37.71	54.43	91.06	8.30

Yunnan-Guizhou Plateau, and due to their elevated terrain, they have cooler climate. They may be considered as relatively "cool" provinces. These climatic differences among five southern provinces influence their respective electricity consumption patterns and vulnerabilities to climate change, necessitating targeted adaptation and mitigation strategies.

Third, there are significant economic and resources differences among these five provinces, implying heterogeneity in electricity demand-supply pattern and potentially impacts of climate change. Guangdong, as the leader in economic development consumes the most electricity among five provinces and its own supply may fall short, necessitating electricity import from the other four provinces. Currently, Yunnan and Guizhou are the exporting provinces due to their abundant hydropower and coal, while Guangxi and Guangdong are the importing provinces. Being the largest and most developed economy in this region, Guangdong accounts for about 98 % of annual electricity imports. Fig. 1 shows that Guangdong imported almost 1/3 of electricity from Yunnan, but they are not implemented on a market base but on a planned base. The existing transmission lines among the southern provinces are critical for facilitating this electricity trade. However, the State Grid Corporation of China has noted that while significant investments have been made in recent years, further upgrades are essential to enhance capacity and reliability.

Fig. 2 gives a first idea of the cross-province differences as determined by the size and technology type of installed production capacities and electricity demand. It shows the empirically observed frequency distribution of hourly electricity demand in 2018 for each province and the marginal technology used if domestic demand were met entirely by domestic production. The horizontal axis plots cumulative capacity or demand (both in GW). There exist sizable cross-province differences due to varying technology mixes. For example, Yunnan uses cheap hydro, Guizhou relies on coal, and Guangdong uses more expensive gas technology. All provinces have excess installed generation capacities, ranging from 56 % to 375 %, based on yearly average demand. Regarding the peak demand, Guangdong is the only province in which demand cannot be met domestically during a small number of hours over the year. With average temperature increases in the future, Guangdong's demand-supply gap will increase, posing a serious energy security problem.

The existing inter-provincial electricity trade was largely administered, directed, and implemented as part of top-level energy strategies, such as the allocation of electricity from major hydroelectric projects (e.g., the Three Gorges Dam) and the west-to-east and north-to-south electricity corridor projects. The planning-based mechanism can often result in inefficiencies due to its inability to quickly adapt to changing market conditions, technological advancements, and consumer demands. Decisions made by centralized authorities might not always align with the most optimal solutions, leading to resource wastage or shortages. Inefficiency is not the only problem of planning-based mechanism; electricity security is also threatened by an inflexible power system.

3. Estimating electricity temperature response function

The changing climate is making global average temperature rising, which not only changes the total electricity demand but also its intra-day patterns. In this section, we estimate the electricity demand-temperature response function for five provinces using a nonlinear statistical model to reveal the impacts of climate change.

3.1. Statistical model

To estimate the response function of average and peak loads to weather, we follow Auffhammer et al. (2017) and estimate a set of time series models, one for each province. Our sample data consist of provincial-level electricity loads at five-minute intervals, which are aggregated to daily frequency when conducting the analysis. Average hourly load is defined as the total daily load divided by 24, and peak load is defined as the maximum hourly load in a day.

We rely on inter-day variation in average load or peak load as a function of daily weather to identify the regression coefficients. We model the electricity demand-temperature response function using a log-linear function for each province and estimate it by using seemingly uncorrelated regression. The richness of our data enables us to document nonlinearities in the response functions. The estimating equation is given by

$$Load_{jt} = \alpha + \sum_{b}\beta_j f_j\left(Temp_{jt}\right) + f_j(t) + \delta P_{jt} + \mu_{dweek} + \varphi_{dmonth} + \varepsilon_t \tag{1}$$

where j represents the province, t is the day of the sample, $Load_{jt}$ is either the average load or peak load for day t in province j, $Temp_{jt}$ is the daily average temperature, $f_j(t)$ is a sixth-order Chebychev polynomial in the day of the sample to capture nonlinearity, and P_{jt} is the total daily precipitation.[1] As electricity consumption tends to be higher over the weekend and varies across months, μ_{dweek} captures the fixed effects for the day of the week, and φ_{dmonth} controls for the fixed effects for the month of the year. The coefficient of interest is β, representing the impact of temperature on daily load.

The functions f_j are spline functions. The nonlinearity of the response function has been well-established in the literature, and we assume that temperature response varies flexibly. Existing studies typically use predetermined bins. However, we use splines because they allow for slopes within bins, thereby smoothing the response function. The smoother response facilitates the implementation of our selection criterion, making it easier to determine the number of knots and produce estimates that avoid spurious detail. Once the number of knots is determined, they are located at equally spaced quantiles, ensuring a comparable number of observations between adjacent knots for slope estimation. Although our daily-aggregated data allows for the estimation of many knots, we are concerned that using too many might capture spurious relationships given the relatively short overall sample period of one year. To address this, we use a 10-fold cross-validation technique to find the optimal number of knots, where further increases no longer improve out-of-sample predictions.

3.2. Estimation results

Fig. 3 and Fig. 4 depict the response functions for daily average/peak load for each province with minimal restrictions imposed on the functional form. Consistent with previous studies (Auffhammer et al., 2017; Zhang et al., 2023), all the response functions show a U-shape curve, indicating that electricity load responds more sensitively to extreme temperatures. However, our research shows more heterogenous results, reflecting distinct responses to temperature increases between "hot" areas and "cool" areas in terms of load.

It shows that the level of responsiveness varies across regions, mainly driven by climate zones. In "hot" provinces (Fig. 3), Guangdong and Guangxi show a similar pattern. The curve is relatively flat between 15 and 25 °C, representing a comfortable temperature zone. Load responds asymmetrically to high and low temperatures; increases are more sensitive to higher temperatures (>25 °C) than to lower temperatures (<15 °C). In Hainan province, there are few days with temperatures below 10 °C; therefore, the curve shows only the right part, rising sharply after 22 °C. In relatively "cool" provinces (Fig. 4), Guizhou and Yunnan, there are few days when temperatures exceed 25 °C, so the curve cannot capture the demand response above that level, showing only the left part. For low temperatures, a one-degree drop significantly

[1] *We measure the provincial daily temperature and precipitation by taking an average of the weather variables from all the stations that are in the province.*

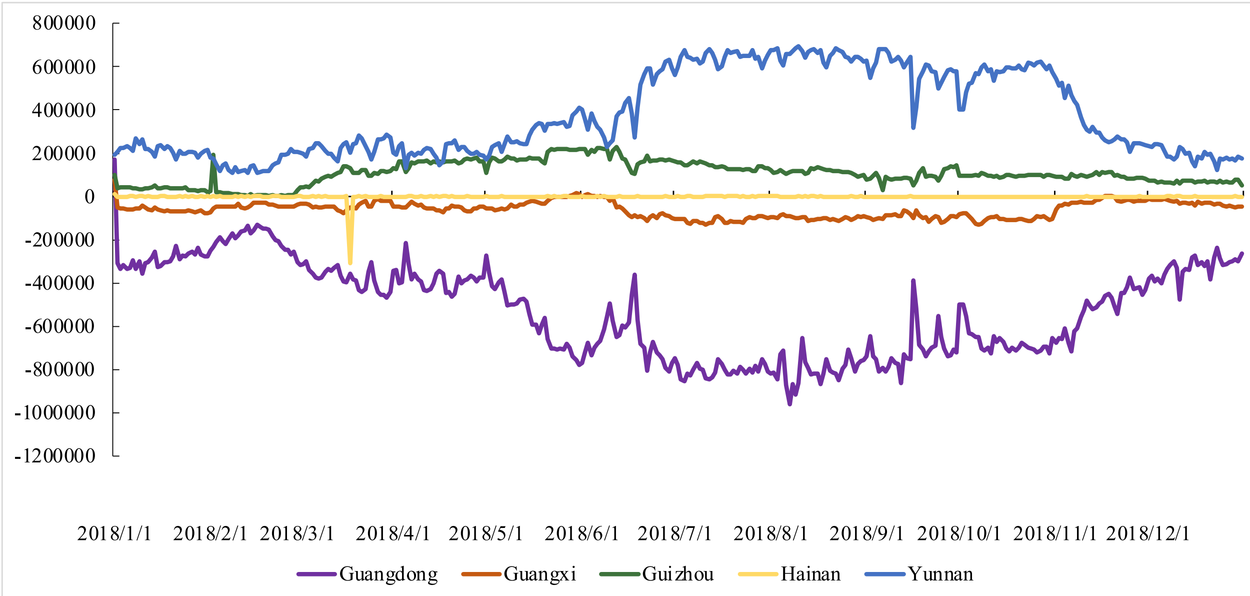

Fig. 1. Difference between power supply and demand (MWh).

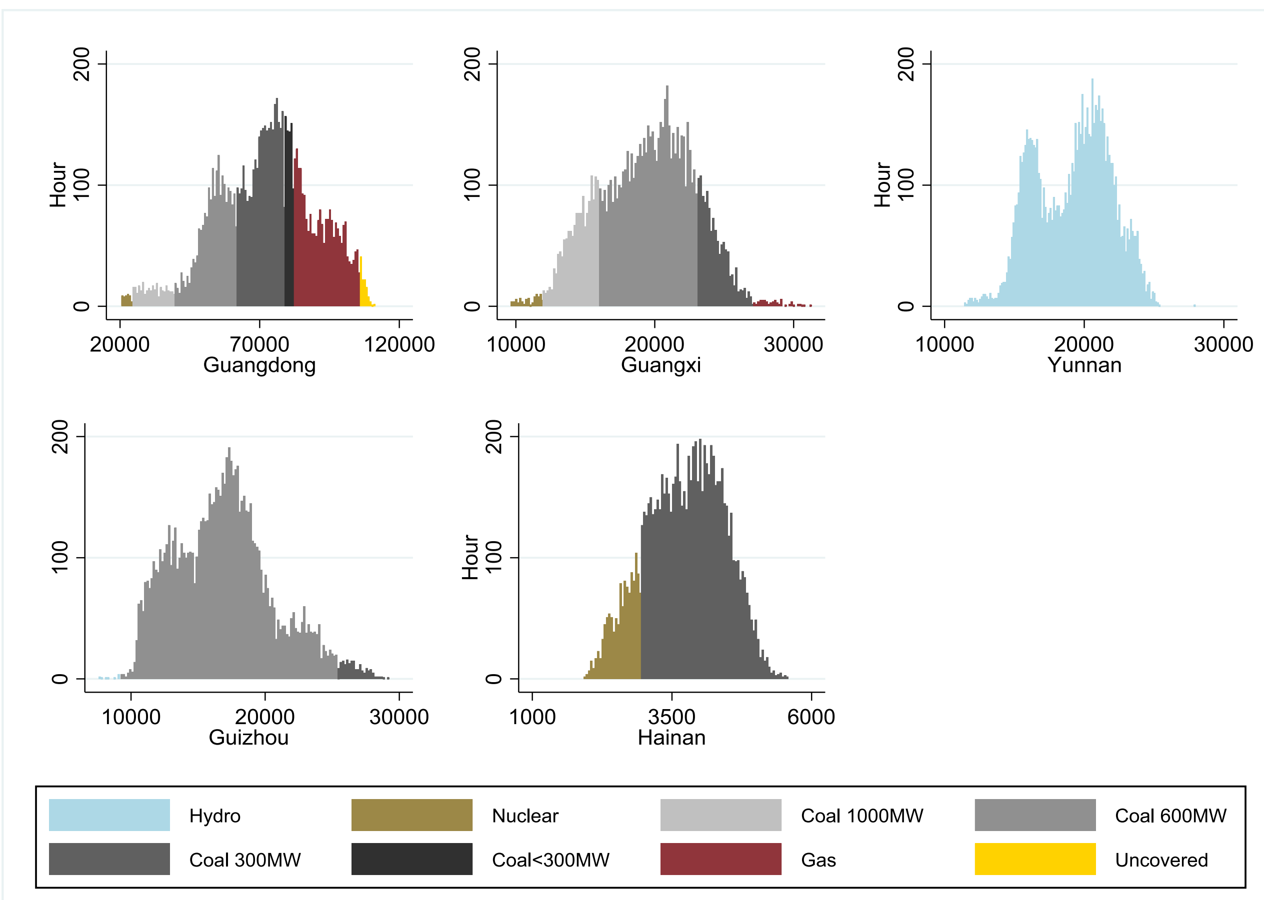

Fig. 2. Frequency distribution of hourly electricity demand.

increases electricity consumption.

4. Simulation of future climate change impacts

In this section, to simulate future climate change impacts, we applied the coefficients obtained from Section 3 to predict future average and

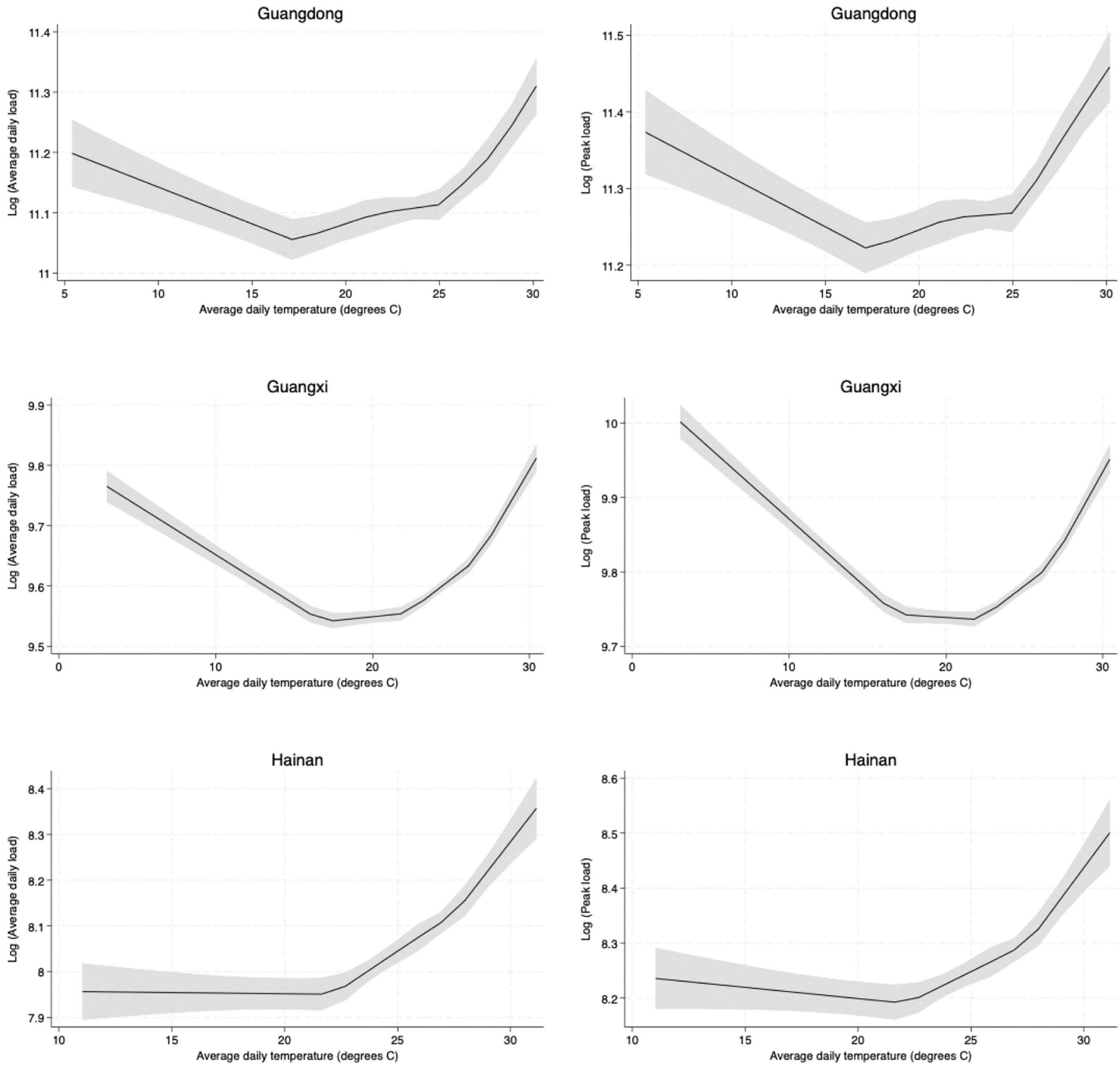

Fig. 3. Temperature response functions for daily average/peak load in "hot" provinces.
Notes: The x-axis represents the daily average temperature, and the y-axis represents the logarithmic values of average/peak load. The grey shading represents a 95 % confidence interval.

peak electricity demand.[2] Considering the heterogeneity among provinces, we also calculate their demand correlations to evaluate whether there are benefits to enlarging the dispatch area and establishing a regional electricity market.

4.1. Simulation method

Following Auffhammer et al. (2017) and Li et al. (2019), we predict the end-of-century climate by calculating the monthly average difference between model projections for 2018 and 2080–2099, then adding that difference to a historical baseline of weather variations. This method provides us a simulated time series of data for each province, adjusted for changes in the mean of the temperature distribution but retaining representative daily variance in temperature. The temperature and precipitation data for the period of 2080–2099 are obtained from the NASA Earth Exchange Global Daily Downscaled Projections dataset. The dataset is comprised of downscaled climate scenarios derived from 21 General Circulation Models (GCMs) conducted under the Coupled Model Intercomparison Project Phase 5 (CMIP5) and includes two of the four greenhouse gas emissions scenarios known as Representative Concentration Pathways (RCPs). Specifically, these scenarios are RCP4.5 and RCP8.5. RCP4.5 represents a pathway where emissions peak around 2040 and then decline, while RCP8.5 represents a scenario in

[2] *We have also conducted a machine learning method (Generalized Random Forest, GRF) as a robustness check. The simulation results are consistent with the U-shape curves.*

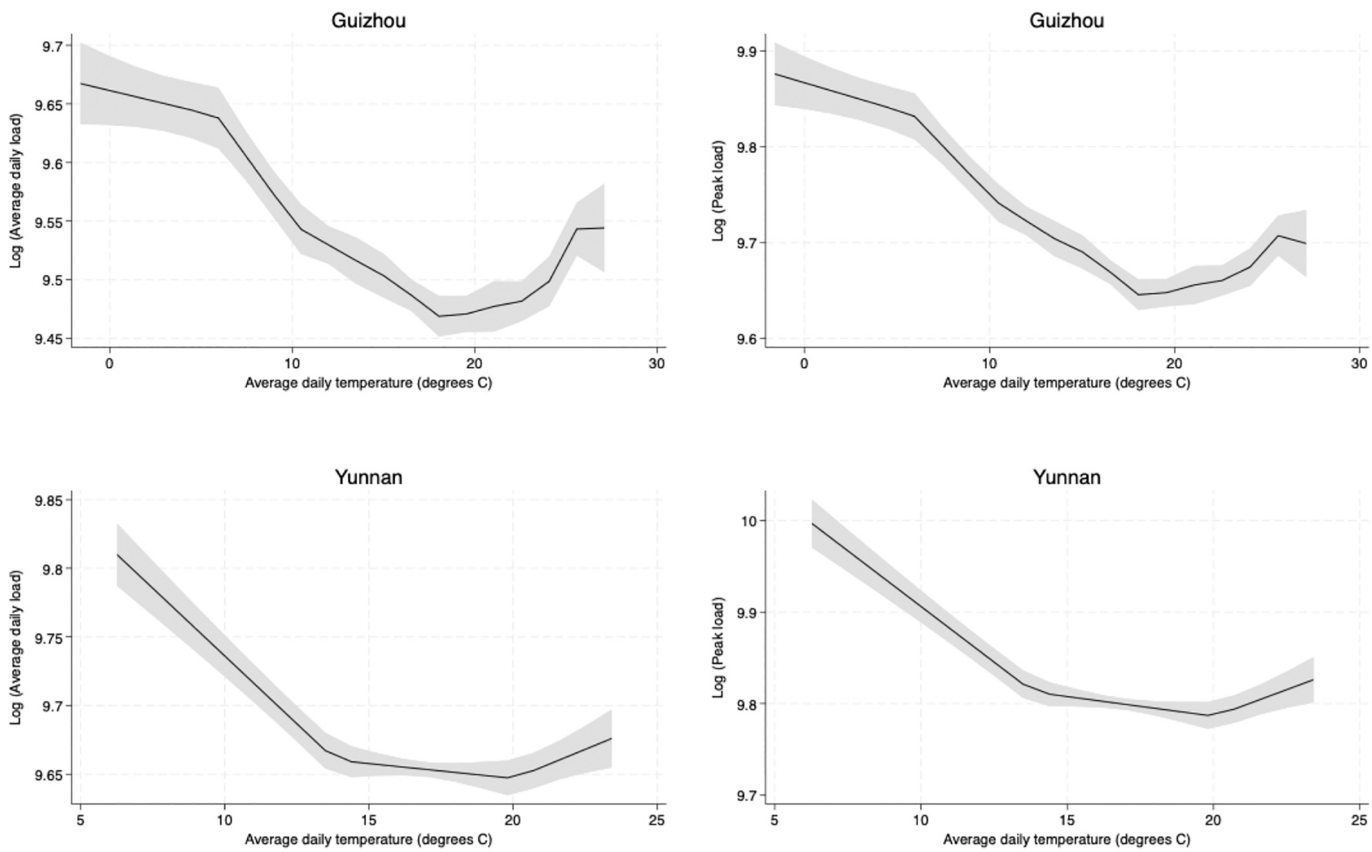

Fig. 4. Temperature response functions for daily average/peak load in “cool” provinces.
Notes: The x-axis represents the daily average temperature, and the y-axis represents the logarithmic values of average/peak load. The grey shading represents a 95 % confidence interval.

which emissions continue to rise throughout the 21st century. Among the four models in which China participated in CMIP5, we use BNU-ESM.

We then apply the coefficients from our estimation model to predict future average and peak electricity demand under different climate change scenarios. To estimate percentage changes, we compare estimates of average and peak loads under two given climate change scenario (RCP4.5 and RCP8.5) and a baseline scenario in which no warming occurs. The considered climate scenarios correspond to the Representative Concentration Pathways and range from ambitious climate change mitigation in line with the Paris Agreement (RCP2.6) to unabated climate change (RCP8.5).

4.2. Simulated results

Combing results from the statistical model and future predictions of climate change, Table 2 summarizes the estimated end-of-century percentage changes in average load (Column 1–4) and peak load (Column 5–8) for RCP4.5 scenario and RCP8.5 scenario. Specifically, Column (1) reports the average change in average load, and Column (5) reports the average change in peak load. Columns (2) and (6) document the average shift in the 95th percentile, while Columns (3) and (7) estimate the percentage change in the number of days with loads greater than the current 95th percentiles. Finally, Columns (4) and (8) estimate the percentage change in the number of days with loads greater than the current 99th percentiles.

The initial examination of the result shows several findings. First, climate change will normalize a higher level of electricity demand. Regardless of the scenarios and loads being considered, the upward shift in the right tail reflects that the upper end of the distribution will “stretch” further outward than the middle, compared to current load distributions. As expected, the RCP8.5 scenario has a greater impact on load distributions than the modest warming of the RCP4.5 scenario.

More interestingly, the results show that the average hourly load responds more strongly than the daily peak load in our sample under both climate change scenarios. On a regional average level, the end-of-century results under the modest warming RCP4.5 scenario predict a 2.85 % increase (column 1) in average hourly load and a 2.16 % increase (column 5) in daily peak load across all provinces due to climate change. A similar pattern is observed under the high climate change RCP8.5 scenario, where average hourly load increases more than daily peak load (6.64 % vs. 5.03 %). This regional outcome is primarily influenced by three “hot” provinces—Guangdong, Guangxi, and Hainan—where the average hourly load responds much more strongly than the peak load. In contrast, the two “cool” provinces, Guizhou and Yunnan, exhibit negative and opposite responses.

This result differs from the findings of Auffhammer et al. (2017), who have found that peak load responds more strongly to increases in temperature in the United States. We speculate the reason may be due to the different adoption rates and usage behaviors of air conditioners. The peak load response is more likely driven by the increased adoption of air conditioning (Auffhammer and Aroonruengsawat, 2011; Auffhammer and Wolfram, 2014; Allen et al., 2016; Auffhammer et al., 2017; Perera et al., 2020). In the “hot” provinces of Southern China, the adoption rates of air conditioner are already very high (1.45 air conditioners/household).[3] Higher temperatures result in longer usage times for air conditioners, which increases the average hourly load.

Finally, and more importantly, the provincial results show

[3] *National Bureau of Statistics of China. (2021). China Statistical Yearbook 2021. Beijing: China Statistics Press.*

Table 2
Increase in average hourly load and peak load by the end of the century.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	%△ average hourly load	%△ 95th percentile average hourly load	%△ frequency days w. average hourly load > current 95th percentile	%△ frequency days w. average hourly load > current 99th percentile	%△ peak load	%△ 95th percentile peak load	%△ frequency days w. peak load > current 95th percentile	%△ frequency days w. peak load > current 99th percentile
RCP 4.5								
Regional average	**2.85**	**5.44**	**168.89**	**966.67**	**2.16**	**2.85**	**130.00**	**566.66**
Guangdong	6.26	15.53	461.11	2700.00	5.22	11.55	427.78	2833.33
Guangxi	6.15	14.92	405.56	2100.00	4.63	7.62	244.44	−66.67
Guizhou	−0.27	−4.32	−38.89	−33.33	−0.51	−4.46	−38.89	−66.67
Yunnan	−0.29	−2.17	−94.44	−100.00	−0.34	−3.65	−88.89	−66.67
Hainan	2.42	3.26	111.11	166.67	1.79	3.17	105.56	200.00
RCP 8.5								
Regional average	**6.64**	**11.37**	**415.28**	**2350.00**	**5.03**	**7.25**	**373.61**	**1525.00**
Guangdong	12.75	26.11	638.89	3966.67	10.34	19.33	572.22	3733.33
Guangxi	12.04	24.67	700.00	4100.00	9.26	15.53	583.33	1133.33
Guizhou	−0.58	−5.67	−50.00	−66.67	−1.46	−6.53	−55.56	−66.67
Yunnan	0.20	−1.27	−83.33	−100.00	0.31	−2.98	−94.44	−66.67
Hainan	8.78	13.00	372.22	1400.00	6.68	10.91	394.44	1300.00

heterogeneous impacts of climate change. Under the modest warming RCP4.5 scenario, the estimates show that the electricity demand in three “hot” provinces (Guangdong, Guangxi and Hainan) is positively affected, while two “cool” provinces (Yunnan and Guizhou) are negatively affected, as they may reduce heating needs in winter. The loads for Guangdong and Guangxi are more dramatically impacted, with an increase in average hourly load of 6 % and a rise in daily peak load of 5 %, while the impact on Hainan is moderate. As RCP8.5 reflects a more pronounced increases in temperature, we find larger percentage changes in all categories. Guizhou’s electricity demand is negatively affected, whereas the other four provinces are all positively affected. With an increase in average hourly load of 13 % and a rise in daily peak load of 10 %, Guangdong will experience the fastest-growing demand, followed by Guangxi (12 % for average hourly load and 9 % for daily peak load) and Hainan (9 % for average hourly load and 7 % for daily peak load).

Fig. 5 and Fig. 6 presents the predicted distributions of end-of-century changes in average and peak electricity demand for five provinces using violin plots. The green plot shows the distribution of average and peak load under present-day temperature conditions. Additionally, the same graph includes predictions from the ensemble of climate models under RCP4.5 (blue) and RCP8.5 (red). The three dots represent the median values.

In the “hot” provinces, all provinces exhibit a bimodal distribution with two peaks, although the bimodality in Guangxi is less pronounced. One peak represents relatively low use, and the other relatively high use, consistent with previous studies (Auffhammer et al., 2017). The low-use mode does not shift substantially for either peak load or average load due to a decrease in the number of days with moderate heating needs, even as the number of days with moderate cooling needs increases. However, since most high-peak days are driven by warmer temperatures, the upward shift in the temperature distribution has a corresponding effect on the distribution of peak load days, driving the second

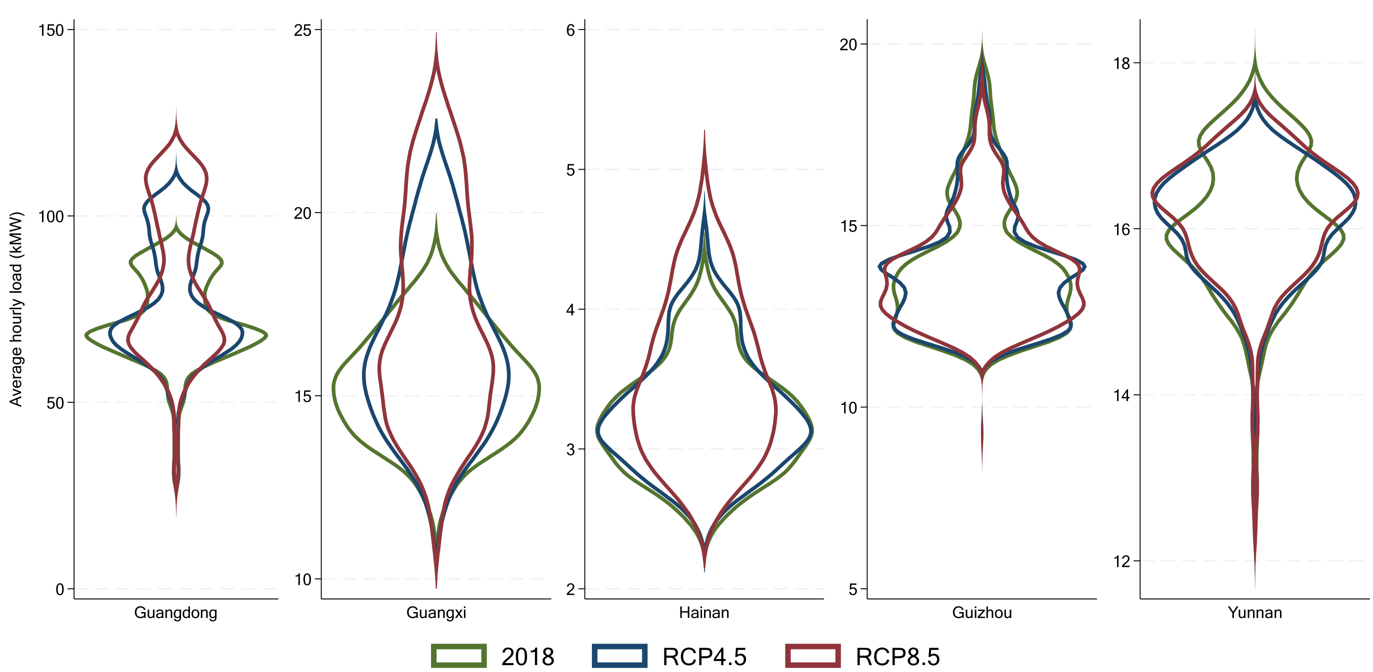

Fig. 5. Climate change shifts the distribution of power demand: Average load.

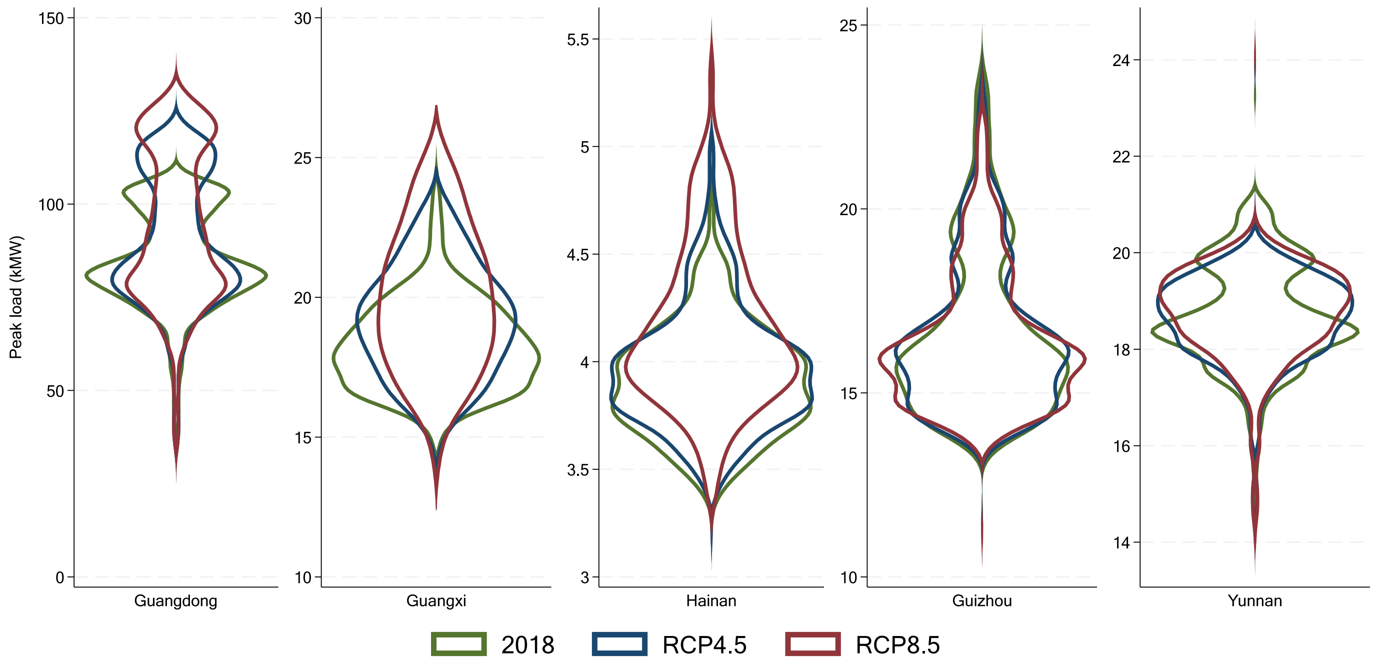

Fig. 6. Climate change shifts the distribution of power demand: Peak load.

mode higher under RCP4.5 and even higher under RCP8.5. In the "cool" provinces, load distributions do not exhibit a distinct pattern. As temperatures rise, the load distributions become more concentrated, with a corresponding decrease in the frequency of higher loads.

4.3. Cross-province demand correlation of electricity demand

The heterogenous demand changes driven by climate change can redirect the inter-provincial electricity trade patterns. The difference between power supply and demand varies considerably across provinces. Intuitively, if demand in province A is low while being high in province B, idle production capacity in A can be used to meet high demand in B. Ceteris paribus, the lower the demand correlation between provinces, the greater the benefits that could be achieved by trading. If inter-provincial demands would be perfectly positively correlated, then smaller trade volumes would be expected for given price inter-provincial differentials. Electricity trade between two provinces is larger when the inter-provincial correlation between demands is lower. As Section 4.2

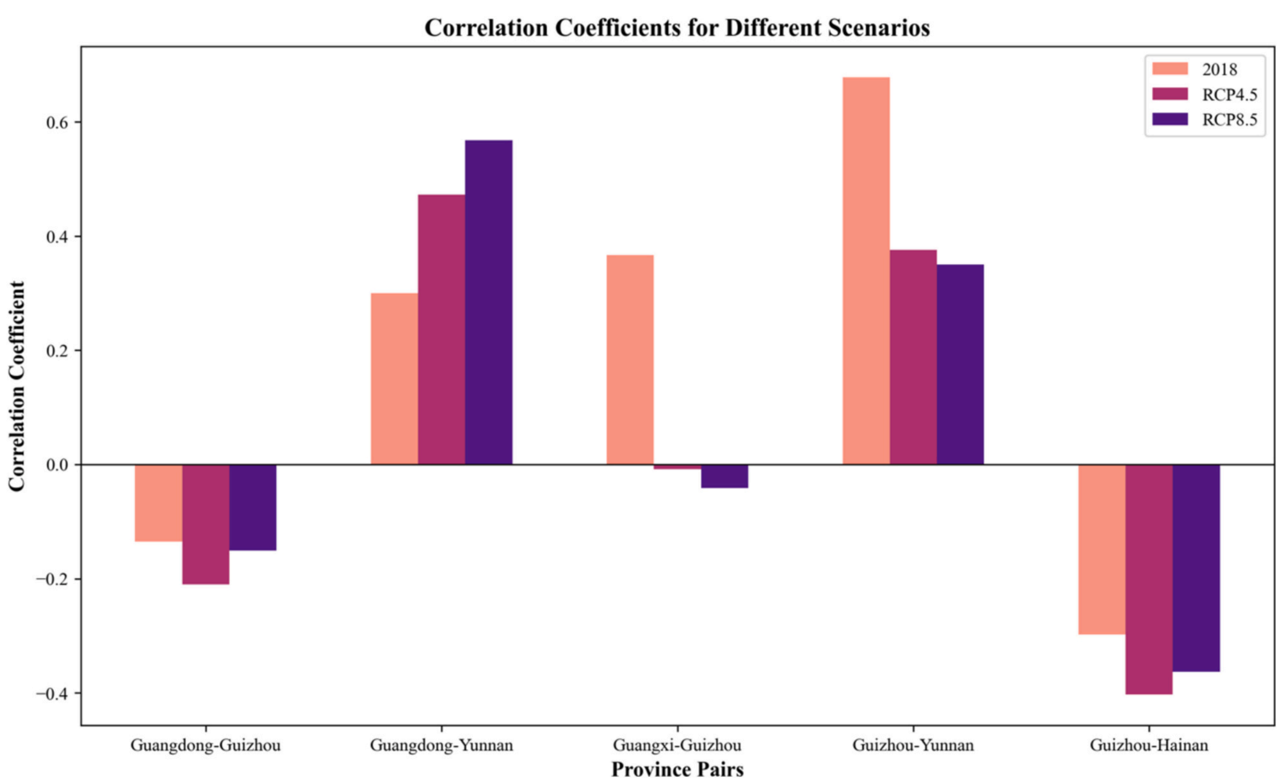

Fig. 7. Daily demand correlation for mean load in weekdays.

showed, rising temperatures will cause electricity loads to increase, and different provinces have shown heterogenous responses towards the climate change. Therefore, their demand correlations may show different patterns, indicating future trading possibilities.

Fig. 7 shows the daily average demand correlation among selective province pairs, which exhibit more dramatic changes or trading possibilities, under three climate change scenarios.[4] Several correlation changes cab be observed from this figure. First, only the Guangdong-Guizhou, Guangxi-Guizhou, and Guizhou-Hainan pairs show negative demand correlations, indicating that trade among these provinces can be complementary. Second, as temperatures rise, the Guangxi-Guizhou correlations shift from positive to negative, while the Guizhou-Yunnan correlation coefficients decrease, suggesting that their trading possibilities are increasing and that trade between them may become more beneficial. Third, although Yunnan is currently the largest electricity exporter to Guangdong, this trend may not be sustainable, as the demand correlation between Guangdong and Yunnan is increasing. The more positive the values, the less possibility for trade among provinces and the fewer benefits from enlarging the regional dispatch area.

5. Estimating the potential benefits of enlarging dispatch area

5.1. Evaluation method

Heterogeneous changes in electricity demand at the provincial level and the associated correlations suggest a potential cost-effective solution by encouraging more inter-provincial trade through expanding the dispatch area. An example such as establishing an EU-wide market has shown that it is more cost-effective than investing in capacity. In this section, we take into account the factors such as demand, supply structure, and transmission line capacity, and we construct a cost-minimizing model to assess the potential cost-effectiveness of expanding the dispatch area.

We first define two scenarios based on the potential reform process of China’s electricity system. The first scenario is “business as usual” (BAU), which represents a non-reform scenario as a benchmark. The second scenario is a regional dispatch area scenario, in which both provincial generation and inter-provincial trade are optimized at a regional level. We simulate the electricity production and trade of each province for three climate conditions under each scenario: climate in 2018, RCP4.5 and RCP8.5. Different climate conditions imply different daily average and peak load. Fig. 8 provides an intuitive understanding of the scenario settings.

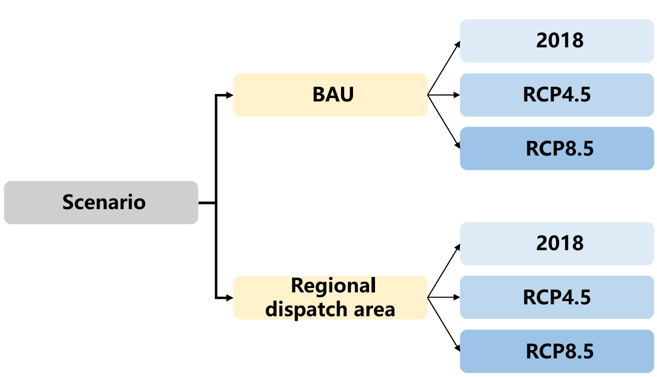

Fig. 8. Regional market analysis scenarios.

In our model, we assume a perfectly competitive partial market equilibrium with inelastic demand. The daily average and peak demand are supplied by minimizing generation costs, subject to physical constraints (e.g., generation capacity, transmission limits, and reserve capacity requirement), as well as different market institutional arrangements. In the BAU scenario, technology-specific marginal costs and installed generation capacities define the supply curve for domestically produced electricity in each province. In the regional market scenario, generation capacity and demand are pooled together to form the aggregated supply and demand curves at the regional level. Daily equilibria are determined by the marginal technology at the regional level, subject to the constraint of a transmission capacity limit. The details of the model are provided in **Appendix A.2**. By comparing the differences between the BAU and regional market scenarios, we can evaluate the potential savings from expanding the dispatch area and assess whether the grid’s flexibility can be improved.

5.2. Evaluation results

Under the BAU scenario, power demand cannot be met by the current installed capacity under RCP4.5 and RCP8.5 in Guangdong. When climate change reaches RCP8.5, the gap between electricity demand and supply during peak load is as large as 42.3 GW. If we choose to adopt the “hard” approach of constructing new power plants, assuming all are renewable energy installations (half solar PV and half onshore wind), and calculating based on average costs of $876 and $1274 per MW,[5] the addition of 42.3 GW of installed capacity would require an investment of $4547.25 million.[6] However, under regional dispatch scenario, we find that the current installed capacity can satisfy the loads of different climate scenarios across the entire southern region. In other words, by adopting “soft” measurement like reforming the electricity sector through economic dispatch and expanding the dispatch area, we can save at least $4547.25 million investment costs, which represents a small but notable fraction of the total infrastructure budget in China.

As shown in Fig. 9, the climate change also induces dramatic changes in inter-provincial trade patterns. First, we observe that Yunnan begins to transmit electricity to Guizhou, and Hainan starts electricity trading with Guangdong, whereas under the BAU scenario, these pairs of provinces have no prior arrangements for trading activities. These results are driven by the changing demand patterns indicated by their correlations, which are consistent with our findings in **Section 4**.

Second, we find that the trading volume between Guangxi and Guangdong is increasing. In the BAU scenario, Guangxi sends only 3.79TWh electricity per year to Guangdong. However, under the regional dispatch area scenario, Guangxi transmits significantly more electricity to Guangdong, despite their high demand correlation. This increase is facilitated by the substantial transmission channel capacity between Guangxi and Guangdong, making it practical for Guangxi to help alleviate Guangdong’s electricity shortfall.

Third, we find that Yunnan will continue to transmit a substantial amount of electricity to Guangdong, reaching up to 145.52 TWh per year under the RCP8.5 scenario, regardless of the increasing demand correlation due to rising temperatures. This outcome is attributed to the current maximum transmission capacity between the two provinces. Despite the increasing correlation, Yunnan is expected to cover the majority of Guangdong’s electricity shortfall based on the objective of minimizing generation costs.

These findings help guide the future grid development plan. Establishing a more flexible inter-provincial electricity trading mechanism will facilitate the efficient distribution of power resources during high demand periods, as some provinces start to transmit electricity to others.

[4] *The correlations of all pair provinces are presented in Appendix. Empirically, the inter-provincial correlation coefficients of daily electricity demand in our sample are significantly below unity. The mean and the standard deviation for the distribution of correlation coefficients in our sample are 0.75 and 0.13, respectively.*

[5] The average costs are from IRENA (2023).

[6] $21.15GW*876\$/MW + 21.15GW*1274\$/MW = 4547.25$ million dollars

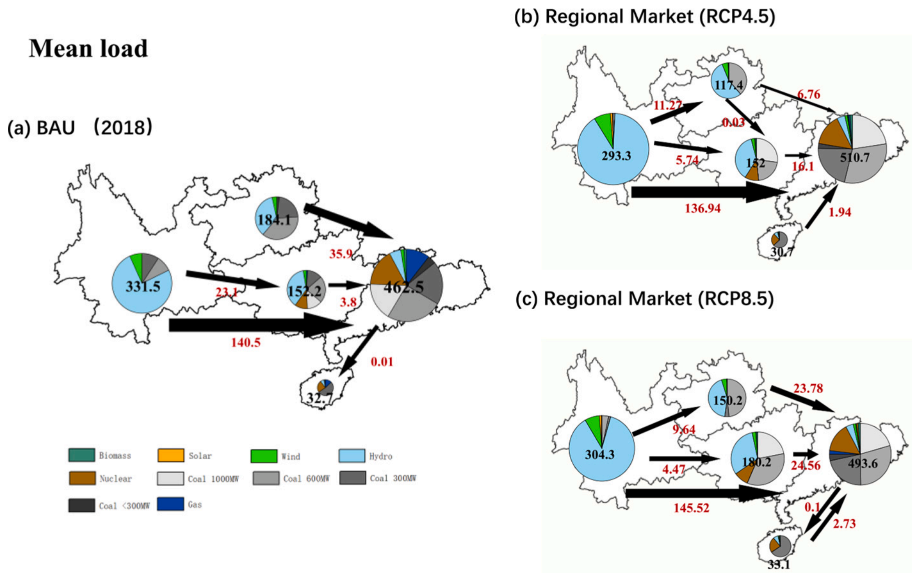

Fig. 9. Power generation and trade in different climate scenarios (mean load).
Notes: All numbers are in TWh.

In addition, expanding existing transmission channels between Guangdong-Guangxi and Guangdong-Yunnan is necessary to ensure sufficient capacity to meet future demand growth.

Fig. 10 illustrates the trade variations in peak load situations among these provinces with rising temperatures. First, different from the mean load situation, inter-provincial trading volumes between Yunnan-Guangdong and Guangxi-Guangdong are much larger, exhibiting high variabilities between mean and peak loads. This suggests that these transmission routes are critical for handling peak demands, while stable routes like Yunnan-Guizhou are not significantly affected by peak load conditions. Second, the total trading volume (210.71TWh) is 31.9TWh larger than the mean load situation (178.77TWh), reflecting the electricity grid's response to ensuring reliability, meeting increased demand, and optimizing economic dispatch. The infrastructure and market dynamics are geared towards accommodating these peaks, demonstrating that the market enhances the grid's flexibility.

Overall, by comparing the model results between the BAU and regional dispatch scenarios, we find that enlarging the dispatch area can effectively fill the demand gap across the entire region, consists with findings from Wang et al. (2019). This approach not only saves a significant amount of investment costs but also increases the grid's flexibility. By enabling provinces to better compensate for each other's demand gaps, the regional dispatch scenario enhances the overall efficiency and reliability of the power grid. This improved coordination ensures that surplus capacity in one area (Yunnan) can be utilized to address shortages in another (Guangdong), leading to a more resilient and flexible electricity system. Wang et al. (2020) also stress that improving the transmission line between Guangdong and Yunnan is the first step to satisfy the demand for electricity.

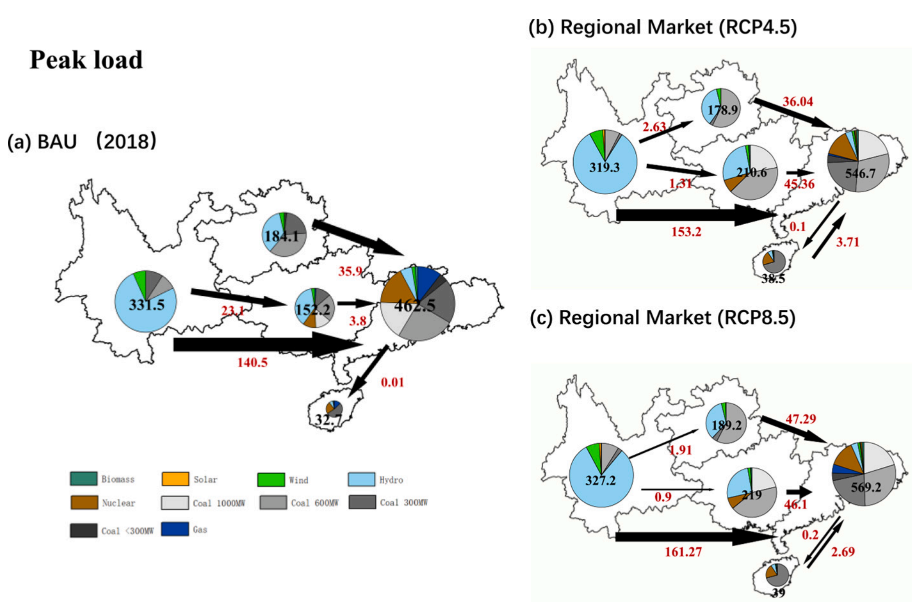

Fig. 10. Power generation and trade in different climate scenarios (peak load).
Notes: All numbers are in TWh.

6. Summary and discussion

Understanding the impact of climate change on electricity demand is essential for both mitigation and adaptation. In this paper, we are the first to use data with better temporal and geographical granularity to reveal that the temperature response functions show different U-shaped curves due to varying climatic conditions among the five Southern Chinse provinces, even though they share similar latitudes. These heterogenous effects could be employed to better adapt to climate change. The findings are summarized as follows.

First, consistent with previous studies in the developed countries, we find a U-shaped relationship between electricity consumption and daily temperature. However, our study shows that each province exhibits different levels of responsiveness due to their climate zones. The "hot" provinces including, Guangdong and Guangxi, display a relatively complete U-curve, while Hainan's curve only includes higher temperatures, rising steeply after 22 °C due to rarely experiencing temperatures below 10 °C. In the "cool" provinces, Guizhou and Yunnan, there are few days when the temperature exceeds 25 °C; therefore, the curve cannot capture demand response above that level, showing only the left half.

Second, combining the estimated response curves with downscaled projections of climate change, we estimate that each 1 °C increase in local mean temperature leads to a 2.85 % increase in average hourly load and a 2.16 % increase in daily peak load under RCP4.5 across all provinces. We observe a noteworthy phenomenon: average load responds more strongly than peak load under both RCP4.5 and RCP8.5 scenarios, presumably driven by the widespread, continuous cooling demand.

Third, as climate change exerts a heterogeneous impact on the electricity demand of different provinces, it creates opportunities for trade and cooperation among these five provinces. Therefore, we anticipate that expanding the dispatch area may help five southern provinces better adapt to climate change. We use a partial market equilibrium model, assuming that system operators implement economic dispatch to minimize total operating costs, to simulate the Southern Grid operation at a daily resolution for different climate scenarios. Our findings demonstrate that enlarging the dispatch area can fill the demand gap across the entire region and increase the grid's flexibility, which the BAU approach cannot achieve. Guangdong can save at least $4547.25 million investment costs by importing electricity as opposed to building more power plants. The changing inter-provincial trade pattern also helps future grid planning.

The increasing adverse impacts of a changing climate on electricity systems highlight an urgent need for action by policy makers, utilities, and relevant stakeholders around the world to enhance their systems' resilience to climate change. Although all countries are affected by climate change, their heterogeneous responses to rising temperatures can be leveraged to jointly address the issue. Global interconnected power grids are proposed as a future concept to facilitate this issue (Chatzivasileiadis et al., 2013; Brinkerink et al., 2019). Integrating different electricity markets across larger regions enables more efficient utilization of low-cost generation capacity, leading to improved cost efficiency in electricity generation. Beyond the cost savings achieved during dispatch, market integration facilitates the sharing of expensive operating reserves and reduces the overall need for generating capacity. Our empirical analysis, conducted across five provinces in southern China, has demonstrated the effectiveness of this approach. Europe has a well-developed network of high-voltage power lines that connect national grids across borders, allowing power to be traded across borders through electricity markets. Southeast Asian countries are learning from this and have already started their electricity interconnections. Cambodia, for instance, has established bilateral power interconnections with neighboring countries such as Laos, Thailand, and Vietnam, through which it imports electricity. Looking ahead, the ASEAN power grid, including China's southern provinces, can contribute to reliable and equitable access to energy and combat climate change together.

This study provides valuable insights into the heterogeneous temperature-electricity response in southern China and the potential for regional market optimization. However, several limitations present opportunities for future research to deepen understanding in this area. First, this study does not incorporate factors such as GDP growth and population changes when considering future electricity demand.[7] Including these economic and demographic drivers in future studies could provide a more comprehensive view of demand dynamics over time. Second, while we analyze regional market optimization, the study does not account for future changes in the generation capacity mix across the five provinces. Investigating how shifts in the power generation portfolio—such as the increased penetration of renewable energy sources—may affect market optimization could yield important insights into system resilience and efficiency.

In addition, future research could explore how climate change may specifically affect electricity transmissions between southern provinces, examining the implications of increasing temperatures on inter-regional electricity flows. This would provide a more comprehensive understanding of adaptive capacity within the power grid and support informed decision-making for future grid planning and regional cooperation.

CRediT authorship contribution statement

Feng Song: Writing – review & editing, Writing – original draft, Methodology, Conceptualization. **Xintong Miao:** Writing – review & editing, Writing – original draft, Formal analysis, Data curation. **Fang Xia:** Writing – review & editing, Writing – original draft, Methodology, Formal analysis.

Declaration of competing interest

None.

Acknowledgments

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[7] *Socio-economic conditions, such as population and GDP, also influence future temperatures. These factors have been incorporated into temperature predictions under RCP 4.5 and RCP 8.5* (Clarke et al., *2007*; Riahi et al., *2007*; Moss et al., *2008*).

Appendix A. Appendix

A.1. Figures and tables

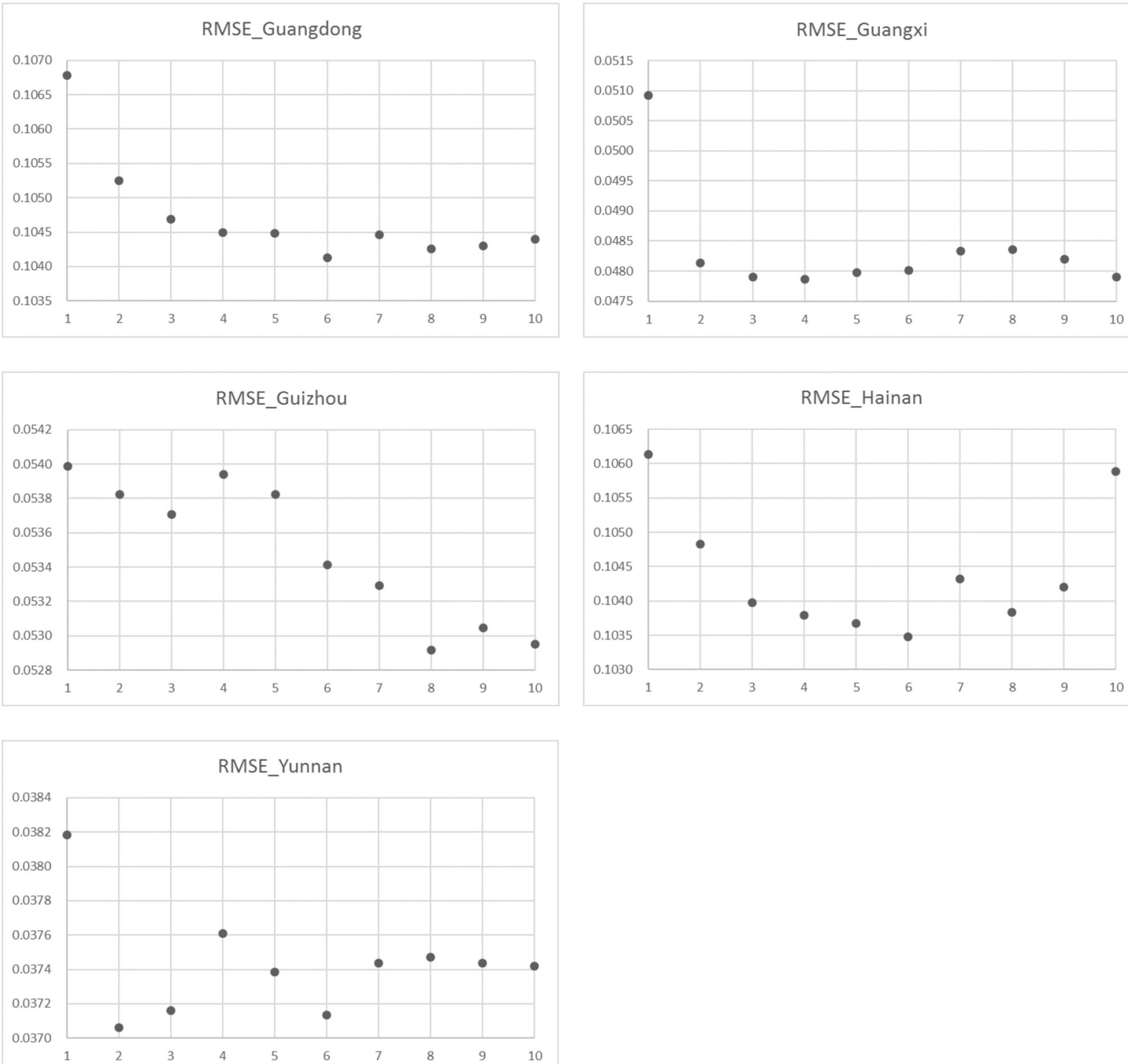

Fig. A.1. Root-mean-square error based on leave-one-out cross-validation.
Notes: The x axis plots the number of knots. We use linear splines for temperature and control for precipitation, day of week fixed effects, month of year fixed effects, and a sixth-order Chebychev polynomial in time.

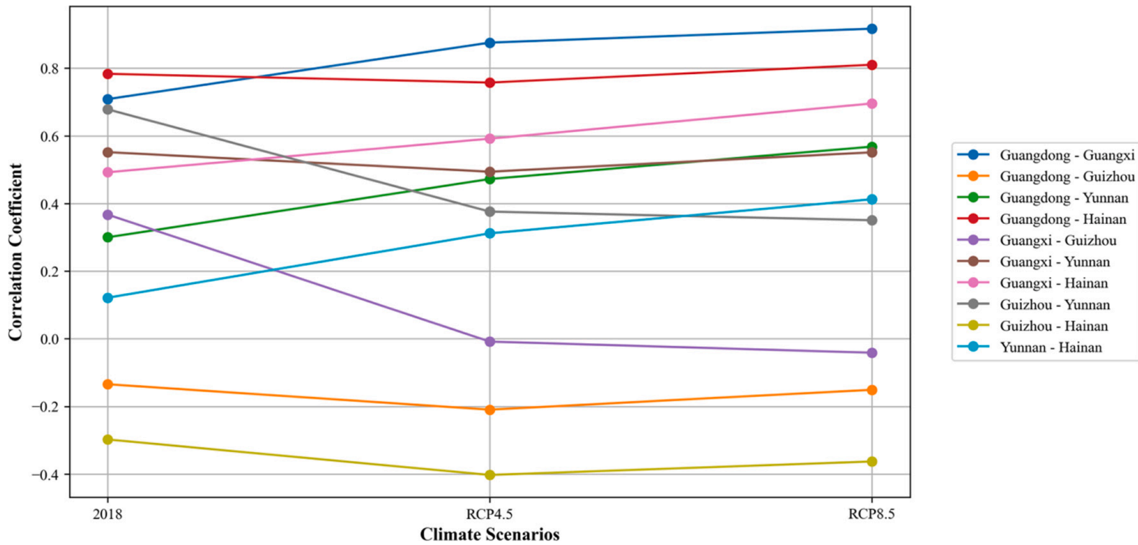

Fig. A.2. Daily demand correlation for mean load in weekdays for all provinces.

Table A1
Impact of temperature on average hourly load (log).

Guangdong		Guangxi		Guizhou		Hainan		Yunnan	
Temperature	−0.012***	Temperature	−0.016***	Temperature	−0.004	Temperature	−0.001	Temperature	−0.020***
< 17.3 °C	(0.002)	< 16.8 °C	(0.001)	< 5.9 °C	(0.003)	< 22.2 °C	(0.003)	< 13.8 °C	(0.001)
Temperature	0.010***	Temperature	0.003	Temperature	−0.021***	Temperature	0.033***	Temperature	−0.002
17.3–21.7 °C	(0.004)	16.8–22.2 °C	(0.002)	5.9–10.3 °C	(0.003)	22.2–25.7 °C	(0.007)	13.8–20 °C	(0.002)
Temperature	0.004	Temperature	0.020***	Temperature	−0.009*	Temperature	0.032**	Temperature	0.009***
21.7–25.2 °C	(0.006)	22.2–26.7 °C	(0.002)	10.3–13.3 °C	(0.005)	25.7–27.5 °C	(0.015)	>20 °C	(0.003)
Temperature	0.031***	Temperature	0.044***	Temperature	−0.009	Temperature	0.064***		
25.2–28.1 °C	(0.007)	>26.7 °C	(0.003)	13.3–15.4 °C	(0.007)	>27.5 °C	(0.010)		
Temperature	0.050***			Temperature	−0.012**				
>28.1 °C	(0.011)			15.4–18.3 °C	(0.006)				
				Temperature	0.004				
				18.3–21.2 °C	(0.005)				
				Temperature	0.003				
				21.2–23.7 °C	(0.006)				
				Temperature	0.037***				
				23.7–25.3 °C	(0.009)				
				Temperature	0.001				
				>25.3 °C	(0.011)				
Observations	365		365		365		365		365
R-squared	0.813		0.824		0.860		0.571		0.731

Notes: We use seemingly unrelated regression. For the time series of each province, we use linear splines for temperature with knots located at equally spaced quantiles determined based on leave-one-out cross-validation (Fig. A.1. 1). We control for precipitation, day of week fixed effects, month of year fixed effects, and a sixth-order Chebychev polynomial in time. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A2
Impact of temperature on peak load (log).

Guangdong		Guangxi		Guizhou		Hainan		Yunnan	
Temperature	−0.013***	Temperature	−0.019***	Temperature	−0.006**	Temperature	−0.004	Temperature	−0.024***
< 17.3 °C	(0.002)	< 16.8 °C	(0.001)	< 5.9 °C	(0.002)	< 22.2 °C	(0.003)	< 13.8 °C	(0.002)
Temperature	0.009**	Temperature	−0.001	Temperature	−0.020***	Temperature	0.020***	Temperature	−0.004*
17.3–21.7 °C	(0.004)	16.8–22.2 °C	(0.001)	5.9–10.3 °C	(0.003)	22.2–25.7 °C	(0.007)	13.8–20 °C	(0.002)
Temperature	0.002	Temperature	0.016***	Temperature	−0.012***	Temperature	0.021	Temperature	0.012***
21.7–25.2 °C	(0.006)	22.2–26.7 °C	(0.002)	10.3–13.3 °C	(0.005)	25.7–27.5 °C	(0.014)	>20 °C	(0.004)
Temperature	0.039***	Temperature	0.038***	Temperature	−0.009	Temperature	0.055***		
25.2–28.1 °C	(0.007)	>26.7 °C	(0.003)	13.3–15.4 °C	(0.006)	>27.5 °C	(0.009)		
Temperature	0.037***			Temperature	−0.016***				
>28.1 °C	(0.011)			15.4–18.3 °C	(0.005)				
				Temperature	0.005				
				18.3–21.2 °C	(0.005)				
				Temperature	0.003				
				21.2–23.7 °C	(0.006)				
				Temperature	0.028***				

(*continued on next page*)

Table A2 (*continued*)

Guangdong		Guangxi		Guizhou		Hainan		Yunnan	
				23.7–25.3 °C	(0.008)				
				Temperature	−0.005				
				>25.3 °C	(0.010)				
Observations	365		365		365		365		365
R-squared	0.808		0.843		0.888		0.301		0.721

Notes: We use seemingly unrelated regression. For the time series of each province, we use linear splines for temperature with knots located at equally spaced quantiles determined based on leave-one-out cross-validation (Fig. A.1. 1). We control for precipitation, day of week fixed effects, month of year fixed effects, and a sixth-order Chebychev polynomial in time. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A3
Impact of a 1 °C increase on electricity consumption.

	Cold Zone	Comfort Zone	Hot Zone
	Elasticity (Temperature rage °C)	Elasticity (Temperature rage °C)	Elasticity (Temperature rage °C)
Guangdong	−0.012*** (<17.3)	0.005 (17.3–25.2)	0.030*** (25–28) 0.050*** (>28)
Guangxi	−0.016***(<16.8)	0.003 (16.8–22.2)	0.020*** (22.2–26.7) 0.044***(>26.7)
Guizhou	−0.021*** (<10.3) −0.009*(10.3–18.3)	−0.006 (18.3–23.7)	0.037***(>23.7–25.3)
Yunnan	−0.024***(<13.8)	−0.009 (13.8–20)	0.009***(>20)
Hainan	No	−0.001(<22.2)	0.033***(25.7–27.5) 0.064***(>27.5)

A.2. Model of regional market benefits analysis

In this section, we will describe a partial equilibrium model to simulate the Southern Grid operation at a daily resolution in five provinces for three scenarios: year 2018, RCP4.5 and RCP8.5.

Power generation: In a perfectly competitive market, electricity firms are assumed to bid their quantities at a marginal cost, where the electricity generation is the decision variable. Coal-fired power generation is operated at the unit level, and the generation units of other technologies are represented in an aggregated way. The total generation of the representative firm using technology $g \in G$ in day $t \in [1, 365]$ in province $i \in \{Guangdong, Guangxi, Yunnan, Guizhou, Hainan\}$ is denoted by $GEN_{t,i,g}$ with a marginal cost of $MC_{i,g}$. The set G comprises coal-fired, gas-fired, nuclear, hydro, wind, solar, and biomass plants. The production of different technologies at any time is constrained by installed capacity:

$$0 \le GEN_{t,i,g} \le (1 - loss_{t,i,g})CAP_{i,g} \; g\epsilon\{coal, gas, nuclear\} \tag{A1}$$

$$0 \le GEN_{t,i,g} \le CAP_{i,g}CF_{t,i,g} \; g\epsilon\{hydro, wind, solar, biomass\} \tag{A2}$$

Where $CAP_{i,g}$ represents the installed capacity using technology g in province i. Due to the different generation feature, we divide the power generation constraints into stable output and variable output. Eq. (A1) represents the stable power generation capacity constraints for coal-fired, gas-fired, and nuclear units. $loss_{t,i,g}$ represents the loss rate calculated from the maintenance rate and the self-consumption rate. The production cannot exceed the power generation capacity after deducting technical losses. Eq. (A2) represents the variable power generation capacity constraints for hydro, wind, solar, and biomass units. $CF_{t,i,g}$ indicates the capacity factor, which is the maximum capacity utilization rate of the technology in each day. Due to the intermittent and periodicity of their power generation technologies, production cannot exceed the installed capacity multiplied by the capacity factor.

Inter-provincial power trade: The trade flow $TRA_{t,i,j}$ from province i to province j in day t is constrained by the transmission capacity $TL_{i,j}$ between the two provinces:

$$0 \le TRA_{t,i,j} \le TL_{i,j} \tag{A3}$$

Without regional market, the inter-provincial trade is determined by inter-provincial contract, while the inter-provincial trade would be liberalized in the regional market. In line with the idea of "iceberg transport cost" (Samuelson, 1954; Krugman, 1991) and the concept of line losses in electricity network models, the proportion of electricity lost in trade between provinces is $line_{i,j}$, and the unit transmission cost is $TC_{i,j}$.

Daily electricity market balance: For province i, total power generation plus net imports is equal to demand at any given day:

$$\sum_g GEN_{t,i,g} + \sum_j [TRA_{t,j,i}(1 - line_{j,i}) + TRA_{t,i,j}] = D_{t,i} \tag{A4}$$

Where $D_{t,i}$ is the demand of province i in day t. $D_{t,i}$ will vary across different climate changing scenarios. We assume that the demand curve is completely inelastic in the short term.

Power dispatch: System operators implement economic dispatch to minimize total operating costs, including power generation costs and transmission costs:

$$min\ Cost = \sum_{t=1}^{365}\sum_{i=1}^{5}\sum_g GEN_{t,i,g}MC_{i,g} + \sum_{t=1}^{365}\sum_i\sum_j TRA_{t,i,j}TC_{i,j} \tag{A5}$$

where *Cost* is the estimated total production cost of the China Southern Grid. Comparing the changes in production cost, we can calculate the potential total welfare gains from market reform and integration.

Appendix B. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.eneco.2024.108115.

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