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Projection of residential and commercial electricity consumption under SSPs in Jiangsu province, China

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Abstract

Future electricity consumption may increase due to climate change, but the amplitude depends on the interaction between many uncertain mechanisms. Based on the linear model and policy model, the residential and commercial electricity consumption in Jiangsu province are projected under the shared socioeconomic pathways (SSPs). The linear model considers climate and socioeconomic factors, and the policy model also takes policy factors into account. We find that the cooling degree days (CDD) coefficient is about 3 times of heating degree days (HDD), which reflects that the cooling demand is much larger than heating, and also shows in the projection. The results of the policy model are generally lower than the linear model, which is the impact of policy factors. For example, the SSP1 and SSP2 of the policy model are 320 TW h and 241.6 TW h lower than the linear model in 2100, respectively. At the end of the 21st century, the residential and commercial electricity consumption in Jiangsu province will reach 107.7−937.9 TW h per year, 1.3−11.6 times of 2010. The SSP1 scenario under the policy model is based on feasible assumptions, and can be used as the target scenario for policymakers to establish energy intensity reduction targets.

Keywords: Electricity consumption; Residential and commercial; Climate change; Projection; SSP

1. Introduction

Energy use is one of the systems most directly exposed to climate change (Schaeffer et al., 2012). Electricity sector has been proved to be more sensitive to ambient temperatures than other fuels, which makes it more vulnerable to climate change (Bauer et al., 2017). Meanwhile, the projection of electricity consumption scenarios is critical for climate mitigation and adaptation (Bauer et al., 2017; Hor et al., 2005; Li et al., 2019).

Previous studies have used different climatic factors to examine the sensitivity of climate change to electricity consumption (Sailor, 1997; Jovanović et al., 2015). Then a large amount of studies has been done on the relationship between climatic-socioeconomic factors and electricity consumption (Fung et al., 2006; Hou et al., 2014). Empirical or regression based models have been constructed to predict the future electricity consumption of different regions with different frameworks. Sailor (2001) developed multiple regression models of degree days, wind speed and enthalpy latent days (ELD) to study the sensitivity of electricity consumption to climate perturbations, and to estimate the response of climate change to residential and commercial electricity consumption in the United States. Lam et al. (2008) used principle component analysis of five climatic variables, dry-bulb temperature, wet-bulb temperature,

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global solar radiation, clearness index and wind speed, and found that subtle but gradual climate change may affect future air-conditioning demand in Hong Kong. Wangpattarapong et al. (2008) selected four climatic factors (cooling degree days (CDD), heating degree days (HDD), rainfall, relative humidity, and wind speed) and three socioeconomic factors (population, income, and domestic shipment of air-conditioner) to construct a function of residential electricity consumption and found that 1 °C temperature rise would lead to 6.79% increase in electricity consumption in Bangkok metropolis. The model built by Cao et al. (2019) discovered that the growth of per capita income drove the growth of 43% of electricity consumption, and carbon pricing and appliance efficiency policies could significantly reduce electricity demand in China. Most models show a good correlation between energy use and climatic and socioeconomic factors.

It is worth noting that most of the previous studies focused on residential and commercial sectors (Lam, 1998; Auffhammer and Aroonruengsawat, 2011; Li et al., 2019), because these two sectors have a better correlation with seasonal variation of temperature comparing with other sectors, mainly due to the change of air-conditioning demand, which is affected by the prevailing weather conditions (Lam et al., 2008). Moreover, it has been proved that the energy consumption of the residential sector accounts for 16%−50% in different countries, 30% in the world's average (Saidur et al., 2007), and less than 20% in China (Zhou et al., 2019). In recent years, China's residential and commercial energy consumption has been increasing rapidly, and the per capita energy consumption is still far lower than that of many developed countries, which is expected to grow further in the future (Zhou et al., 2019).

The modeling methods in the above works can be roughly divided into two distinct approaches: top-down and bottom-up (Swan and Ugursal, 2009). Top-down models uses statistical method to regress energy consumption as a function of top-level variables, for example, macroeconomic factors and climate change. Bottom-up models uses engineering method to extrapolate the energy consumption estimates of a group of representative individuals to the regional level. Most studies use either a top-down (Hor et al., 2005; Mirasgedis et al., 2006; Wenz et al., 2017; Li et al., 2018) or a bottom-up approach (Saidur et al., 2007; Kavousian et al., 2013; Cao et al., 2019). The top-down and bottom-up approaches both have merits and demerits. Top-down approaches are easy to develop based on macro factors, but they will falter when technology breakthrough. Bottom-up approaches have the capability to determine the impact of new technologies, but they are difficult to build on the fact that it requires a large number of survey samples to develop diverse sets of energy profiles.

Besides, some models only focus on the impact of climatic factors without considering the impact of socioeconomic factors (Pardo et al., 2002; Giannakopoulos et al., 2015; Auffhammer et al., 2017). Other models take climatic and socioeconomic factors into account but the prediction of the future scenario is only based on the assumption of one socioeconomic scenario (Hor et al., 2005; Wangpattarapong et al., 2008; Hasegawa et al., 2016). Previous studies have proved that energy use strongly correlated with socioeconomic factors such as household income, electricity price, gross domestic product (GDP) (Hasegawa et al., 2016; Ma et al., 2016). Therefore, the reliable data of future socioeconomic scenarios is also crucial for forecasting electricity consumption.

In recent years, some researches have attempted to construct models on a global scale with reference to Shared Socioeconomic Pathways (SSPs) scenarios (Cian and Wing, 2017; Levesque et al., 2018; van Ruijven et al., 2019). van Ruijven et al. (2019), studying on the global scale, predicted future energy use by income and degree days, based on the projections of spatial population and national income under five socioeconomic scenarios and climate change for two emission scenarios. However, the adoption of a unified model did not consider the different climatic zones and local economic conditions in different regions. Although the projections were comprehensive and capable for comparison among different regions, the data accuracy was insufficient to provide local policy basis for specific regions.

Projection of future energy use is highly relevant to policymakers, meanwhile, future emission reduction target will in turn require policy design. However, most regression models are based on top-down method, which can only take macro factors into consideration (Swan and Ugursal, 2009), limiting their values for policymakers. The impact of policy on the progress of technology adoption is usually considered in bottom-up method (Cao et al., 2019; Zhou et al., 2019). Zhou et al. (2019) put forward feasible energy-saving path and policy suggestions through the combination of top-down and bottom-up models, so as to achieve China's emission reduction target in the Paris Agreement.

In this work, we combine a scenario framework and project the electricity consumption of residential and commercial sectors in Jiangsu province under SSPs. Because of the similar climate zone and economic conditions, the results could be extended to other regions in the Yangtze River Delta, which is the only world-class city cluster and the largest economic zone in China. Meanwhile, Jiangsu province is in the center of the Yangtze River Delta and it is also the second largest GDP among China's provinces, which may reflect China's future development pattern. We construct linear model and policy model. The linear model considers climatic and socioeconomic factors and establishes a top-down multiple regression model. The policy model also takes policy factors into consideration and establishes different policy models to match the SSP scenarios with the combination of top-down and bottom-up approach.

2. Methodology

2.1. Data

2.1.1. Historical data

The period of historical modeling is 2009−2017, because the monthly electricity data is only available in this period. The data of monthly electricity consumption is taken from National Energy Administration and Prospective Research Institute. In prefecture-level cities, monthly electricity consumption data of residential and commercial sector can only be obtained in Nanjing, Wuxi, Changzhou, Zhenjiang, and Huai'an cities. Social and economic data, such as GDP, population, urbanization rate; and air-conditioner ownership, are obtained from China Statistical Yearbook 2009−2017 (NBSC, 2009−2018). The earlier data on the air-conditioner ownership is not statistically comparable until 2013. In terms of climate data, daily mean temperature comes from the observation data of the 15 automatic meteorological stations in the National Meteorological Information Center.

2.1.2. Future data

The period of future projection is 2018−2100. In this study, future scenario depends on the change of the shared socioeconomic pathways (SSPs) (Bauer et al., 2017). The socioeconomic data is obtained from Jing et al. (2019), who predicted GDP, population and other data of different provinces in China under different SSPs. As for temperature, we use downscaled simulations of four models, including BCC-CSM2-MR by Beijing Climate Center of China (BCC), CESM2 and CESM2-WACCM by the National Center for Atmospheric Research of the United States (NCAR), and MRI-ESM2-0 by Meteorological Research Institute of Japan (MRI). The four models have the latest daily mean temperature data under the SSPs, with a resolution of 100 km × 100 km, which participate in the Scenario Model Intercomparison Project of the Coupled Model Intercomparison Project, Phase VI (Neill et al., 2016, https://esgf-node.llnl.gov).

2.1.3. Evaluation of CMIP6 model

The time period for model evaluation is from 2003 to 2012, which we regard as the evaluation period. This is because historical model data is only available before 2014, so we choose an appropriate ten-year period. We define 30°−34°N and 118°−122°E as the range of Jiangsu province, and select the daily average temperature of 15 automatic meteorological stations within the range as the observation data (Fig. 1).

We calculated the Root Mean Square Error (*RMSE*), Mean Absolute Error (*MAE*) and R^2 between the four models and multi-model ensemble mean and the observation data. According to the evaluation results, the *RMSE* and *MAE* of the multi-model ensemble mean are smaller, that is, the deviation is smaller; the R^2 is larger, that is, the correlation is higher. So the multi-model ensemble mean is the best choice to represent future climate change.

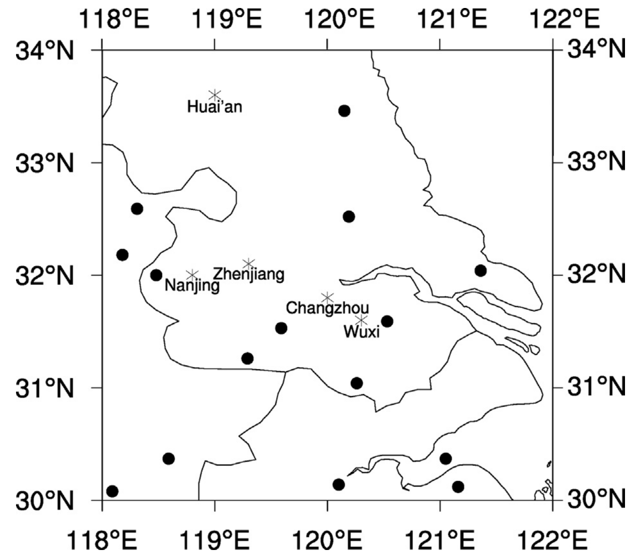

Fig. 1. The spatial distribution of 15 observation stations in Jiangsu province.

2.2. Model framework

Linear model and policy model were constructed to estimate residential and commercial electricity consumption. The linear model, based on top-down multiple regression method, considering climatic-socioeconomic factors according to Wangpattarapong et al. (2008), including cooling degree days (CDD), heating degree days (HDD), gross domestic product (*GDP*), population (*POP*), and urbanization rate (R_u). The policy model, a combination of top-down and bottom-up methods, taking into account the policy factors with additional variable, urban and rural air-conditioner ownership. Two models are established to quantify the impact of policy factors on future electricity consumption scenarios and provide reference for policymakers.

The concept of our model is based on a good correlation between electricity consumption and climatic and socioeconomic factors. For the policy model, we also take policy factors (prefecture-level cities scenario) into account. The best fitting coefficient is selected using the smallest *RMSE* value and the largest R^2 value. In future period, we use the established linear models and input the future data under different SSPs to project future electricity consumption.

The residential and commercial electricity consumption is divided into three sectors (urban residential, rural residential, and commercial), and each sector has two parts (non-fluctuating part and fluctuating part). The historical data analysis shows that the fluctuation trend of electricity consumption is highly consistent with that of CDD and HDD, so it is named fluctuating part, which is jointly controlled by climatic and socioeconomic factors. It is assumed that the electricity consumption of the fluctuating part is all from the air-conditioner. We believe that the non-fluctuating part is controlled by socioeconomic factors, which means that all the non-fluctuating electricity consumption is directly affected by socioeconomic factors.

2.2.1. Linear model

In this part, based on the relationship between electricity consumption and climatic and socioeconomic factors, the multiple linear regression model is established, and the monthly and annual variables are combined in the model. The regression models all depends on climate factors (CDD, HDD), and socioeconomic factors (*GDP*, population (*POP*), and urbanization rate (R_u)). The general form used in this model is:

$$E = (b_0 + b_1 \times R_u + b_2 \times \text{HDD} + b_3 \times \text{HDD} \times R_u + b_4 \times \text{CDD} + b_5 \times \text{CDD} \times R_u) \times GDP / POP \quad (1)$$

where E is the trend-adjusted per capita monthly electricity consumption (in kW h), annual GDP is in million CNY, annual POP is in capita. CDD and HDD, are monthly totals of the traditional cooling and heating degree days (°C d) (Sailor, 2001).

The reference temperature is 22 °C for CDD and 15 °C for HDD based on a research work for Shanghai, which clearly showed a U-shape sensitivity between daily mean temperature and electricity consumption in residential and commercial sectors at these two temperatures (Li et al., 2019). The threshold of 15 °C for HDD means that people will turn on the air conditioner for heating only when the temperature is lower than 15 °C; conversely, the threshold of 22 °C for CDD means that people will turn on the air conditioner for cooling only when the temperature is higher than 22 °C.

Table 1 lists the model coefficients for the five sectors. The correlation coefficient is quite high, with an average of 90%, which can prove that the model fits well with the actual electricity consumption. Besides, whether in urban residential or rural residential sector, the coefficient of climatic factor (b_2, b_4) is greater than that of commercial sector, which means that the residential sector is more sensitive to climate change than the commercial sector. Another important feature is that the coefficient of CDD (b_4) is about 3 times of HDD (b_2) in all sectors, which means that the electricity consumption of cooling is much more sensitive to the temperature as compared to heating.

2.2.2. Policy model

In the linear model, we only consider climatic and socioeconomic factors and establish a multiple regression model, which is a total top-down method. The policy model is optimized on the basis of the linear model, and the influence of policy factors is considered. The prediction of non-fluctuation part adopts the top-down method, while the fluctuation part adopts the bottom-up method, based on the energy consumption scenarios of each prefecture-level city.

Table 1
Coefficients for monthly per capita electricity consumption of different sectors (kW h per capita).

Sector	b_0	b_1	b_2	b_3	b_4	b_5	R^2	*RMSE*
Urban Residential	315	0	0.76	0	2.44	0	0.88	0.71
Rural Residential	675	0	1.18	0	3.8	0	0.85	0.64
Commercial	700	0	0.56	0	1.96	0	0.92	0.98
Residential	675	−360	1.18	−0.42	3.8	−1.36	0.88	1.25
Residential & Commercial	1375	−360	1.74	−0.42	5.76	−1.36	0.95	1.53

The SSPs have been designed as different combinations of challenges to climate change mitigation and adaptation. These paths are interpreted as quantitative scenarios, and are the basis of many studies dealing with long-term projections (Levesque et al., 2018; van Ruijven et al., 2019). We refer to the four SSP scenarios, including SSP1, SSP2, SSP3 and SSP5, and consider that different scenarios have different development patterns (Bauer et al., 2017). In SSP1, the world is gradually moving towards a more sustainable development due to technological development, lifestyle changes and policies supporting energy efficiency improvements. In SSP2, energy intensity improvements continue at historical growth rates and technological improvements are medium. SSP3 is a rocky road, with frequently regional conflicts, ethnic issues, regional competition and other issues. The focus of policy is gradually turning to security issues and technological improvements are slow. In SSP5, energy demand growth is closely coupled with economic growth, and energy consumption grow rapidly and unrestricted.

We construct the policy model based on provincial level (Jiangsu) SSPs and the representative cities for SSP1 and SSP2- Huai'an and Zhenjiang. The modeling period of the policy model is 2013−2017, because the air conditioning ownership data is only available after 2013. In non-fluctuating part (Fig. 2a−c), we adopt the top-down method. We found that in non-fluctuating part, Huai'an city had the best performance in per capita electricity consumption of different sectors, followed by Zhenjiang city, which means these two cities have better energy conservation measures in terms of policies, so we take them as a reference for political influence (The performance of different cities has shown in Appendix Fig. A1). We assume the future energy consumption scenario of SSP3&SSP5 to be based on the linear growth of the historical trend of Jiangsu province, SSP2 to be based on the logarithmic growth of the historical trend of Jiangsu province that eventually reaches the historical value of Zhenjiang city, and SSP1 to be based on the polynomial growth of historical trend of Jiangsu province that eventually reaches the historical value of Zhenjiang and the future value of Huai'an's extrapolation with logarithmic trend.

For the fluctuating part, we assume that the electricity consumption is entirely due to the use of air conditioning, and use the bottom-up method to study (Fig. 2d). This accords with the characteristic that the CDD coefficient is about three times that of HDD in the linear model. We also find that while the cooling sensitivity between cities and the provincial level follows a reasonably same trend, the heating sensitivity of Jiangsu province is significantly lower than that of Zhenjiang and Huai'an. This is because in northern Jiangsu, commercial buildings tend to apply centralized heating with heat source from fossil fuel combustion instead of using electricity as the intermediate energy carrier. Thus, the heating sensitivity for commercial sector is less certain than the cooling sensitivity.

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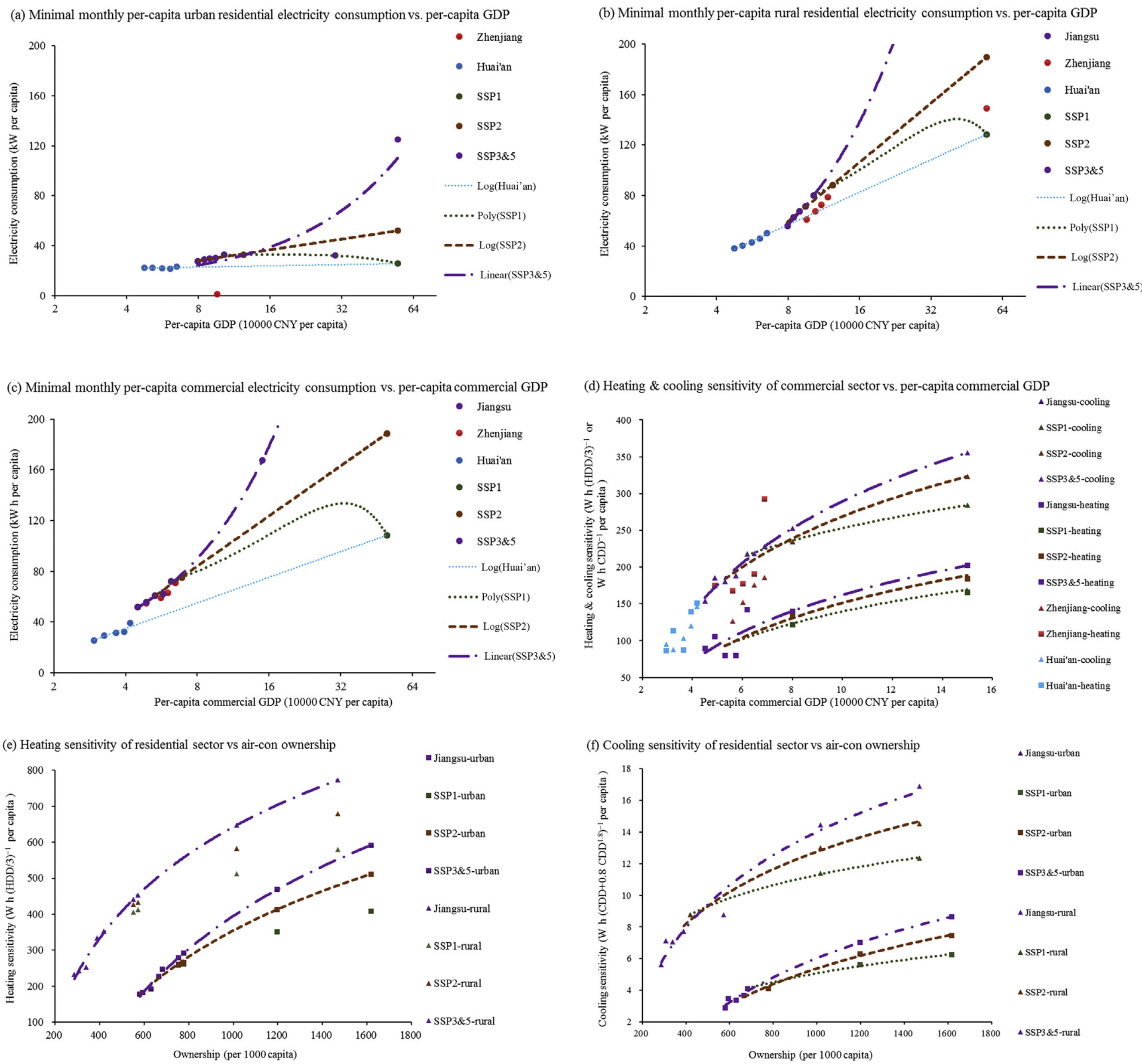

Fig. 2. Projection of electricity intensity (a–c) and sensitivity (d–f) in policy model, (a) non-fluctuating part of urban residential sector, (b) non-fluctuating part of rural residential sector, (c) non-fluctuating part of commercial sector, (d) fluctuating part of commercial sector, (e) fluctuating part of residential heating, and (f) fluctuating part of residential cooling.

Fig. 2e and f shows heating sensitivity and cooling sensitivity in residential sector, respectively. The cooling sensitivity does not have a linear relationship with CDD, but a quadratic relation. This is because both the electricity consumption of air conditioning per residence and the percentage of residence who turn on air-conditioners will increase with temperature, so we adjust the equation and get the most reasonable relationship ($CDD + 0.8CDD^{1.8}$).

For the future scenario in the fluctuating part, we use the bottom-up method. In SSP3&SSP5, the sensitivity is projected from extrapolation of the historical data at provincial level with a logarithmic growth, which implies a gradual saturation of per capita electricity usage for air-conditioning even with increasing air-conditioner ownership (Levesque et al., 2018). In SSP2 and SSP1, the sensitivity will reduce by 10%–15% and 25%–30%, respectively, below the SSP3&SSP5 scenarios. The saving in SSP1&SSP2 can be realized through policy and technology driven use of energy-saving air conditioning, such as revision of air-conditioner efficiency standards. Compared with the bottom-up research results in China (Zhou et al., 2019), the assumption of efficiency improvement in this study is relatively easy to realize.

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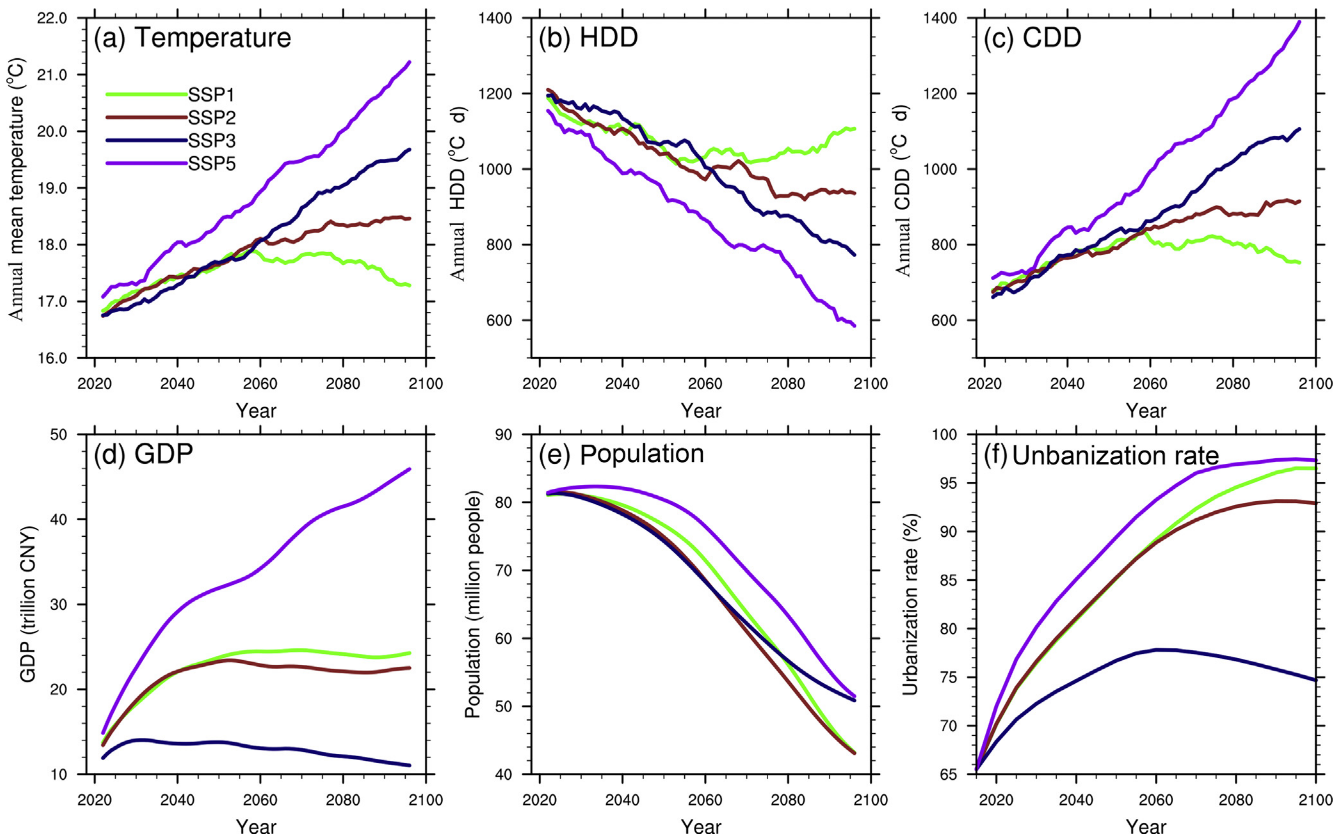

Fig. 3. Socioeconomic and climate change scenarios from 2018 to 2100 under SSPs (The data has been smoothed except for the urbanization rate).

3. Results and discussion

3.1. Scenarios of macro-drivers

The macro-drivers under four SSPs in Jiangsu province are shown in Fig. 3. In terms of annual mean temperature (Fig. 3a), except for SSP1, which shows a downward trend after 2050, other paths show a continuous upward trend. For SSP5 with highly developed fossil fuels, the temperature rise is sharpest. The growth trends of SSP1, SSP2, and SSP3 are quite similar before 2050, and the mean temperatures in 2050 are about 17.5 °C, 1.5 °C higher than that of evaluation period (2003−2012). By 2100, the range of annual mean temperature will be 17.4−21.7 °C, of which the maximum value, SSP5, will be 5.7 °C higher than that of evaluation period. The future trends of HDD (Fig. 3b) and CDD (Fig. 3c) reflect not only the effect of global warming, but also the changing demand for air conditioning. For HDD, all scenarios consistently decline except SSP1 has a reverse trend after 2050. For CDD, SSP3&SSP5 grow rather linearly but at different rates, while SSP1&SSP2 will maintain similar growth until 2050. Beyond that the growth in SSP2 slows down and the trend in SSP1 will reverse. By the end of the 21st century, the value of HDD will be from 554.5 to 1073.2 °C d while the value of CDD will be from 791.9 to 1492.1 °C d.

For the growth trend of GDP (Fig. 3d), SSP5 shows a linear growth, SSP1&SSP2 shows similar, with logarithmic growth, while SSP3 shows a trend of first rising and then declining. By the end of the 21st century, the range of GDP will be 10.7−47.3 trillion CNY, which are 1.5−6.6 times that of 2015. Growth in 2100 compared to 2050, SSP1&SSP2 is similar and basically flat, with SSP3 decreasing by 24% and SSP5 increasing by 48%. In terms of population (Fig. 3e), all paths show a downward trend. By the end of the 21st century, SSP1&SSP2 will decrease to 40 million people, accounting for about 50% of 2015, while SSP3&SSP5 will decrease to 50 million people, accounting for about 60% of 2015. As for urbanization rate (Fig. 3f), except for SSP3, which shows a downward trend after 2060, other paths show a continuous upward trend. By the end of the 21st century, the urbanization rate of SSP1 is 96.5%, SSP2 92.9%, SSP3 74.7%, and SSP5 97.3%. It can be understood that the urbanization rate of SSP5 is the highest due to its unlimited growth path.

3.2. Electricity consumption

Fig. 4 shows the results of annual electricity consumption under four SSPs and two models, which are divided into five different sectors: the non-fluctuating part of urban residential sector (NF-UR), the non-fluctuating part of rural residential sector (NF-RR), the non-fluctuating part of commercial sector (NF-C), the fluctuating part of cooling sector (F-CDD), the fluctuating part of heating sector (F-HDD). The total electricity consumption of residential and commercial sectors will

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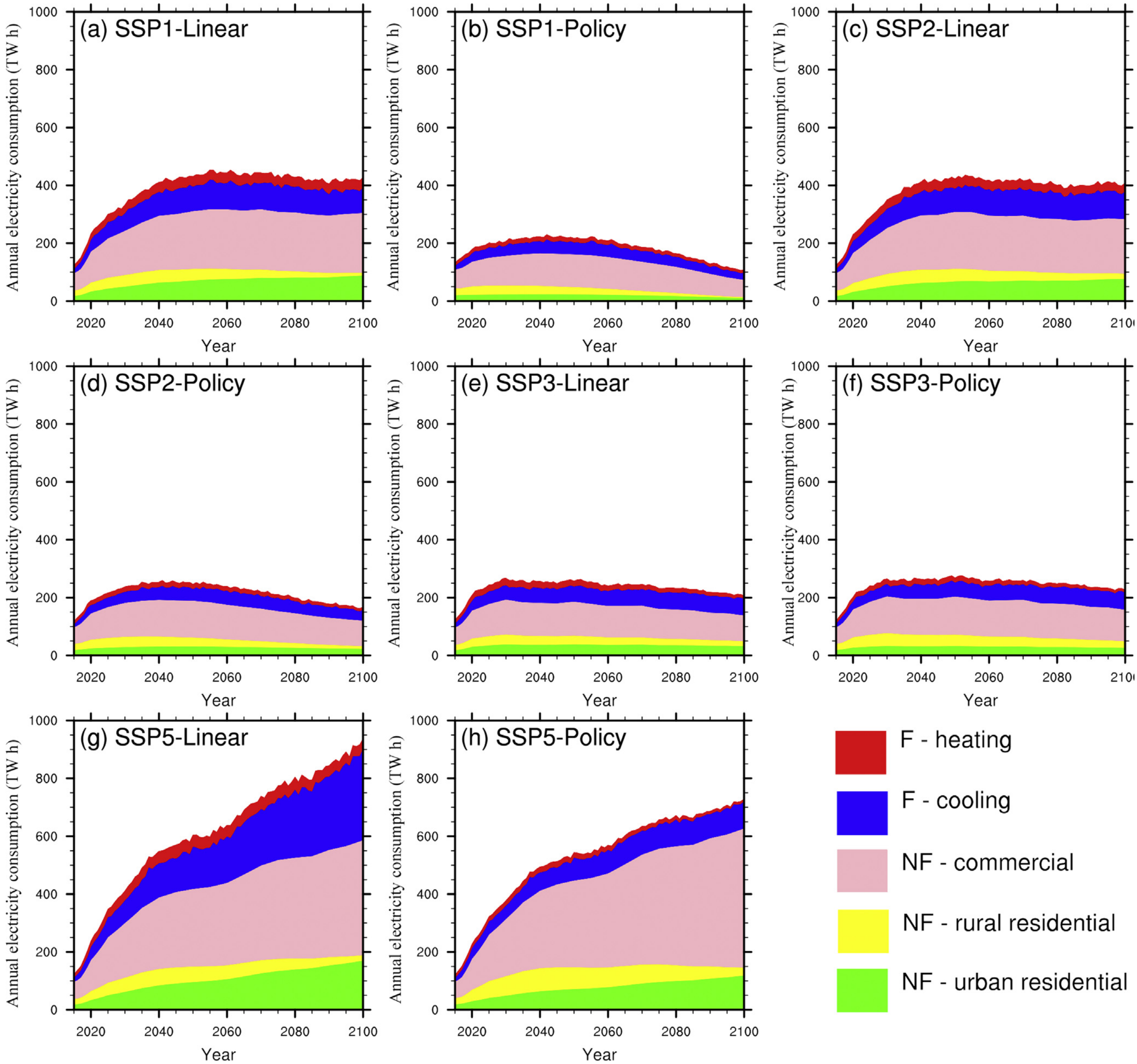

Fig. 4. Annual electricity consumption (TW h per year) of each part (in 2015−2100) (NF is non-fluctuating part and F is fluctuating part).

increase from 81.2 TW h in 2010 to 217.6−605.1 TW h per year in 2050. This translates to 2840 (SSP1-policy) − 7529 (SSP5-linear) kW h per capita per year. See Appendix Fig. A1 for the estimated breakdown of per-capita electricity consumption in 2050 and 2100 under various SSPs.

The SSP1 per-capita electricity consumption in the policy model is comparable to a fully bottom-up study by Zhou et al. (2016), which lays out a roadmap achieving 2800 kW h per capita per year electricity consumption of Chinese buildings by 2050, with electrification raising the percentage of electricity in total end-use energy from 22% in 2010 to 66% in 2050. In that study, the saving potential can be realized through cost-effective energy-efficient technologies, existing building retrofits, integrative designs, and smart systems, with policy recommendations in four areas: disclosure and transparency, market forces, financing and investment, and codes and enforcement. These recommendations generally align with what the SSP1-city, Huai'an, has kept doing in recent years: Huai'an Municipal Bureau of Housing and Urban-Rural Development publicly announced the breakdown of measurable green building task list for its counties, and named the non cooperative buildings and construction companies. Therefore, the combined top-down and bottom-up policy model can also be seen as a simplified bottom-up model, which lumps the consumption of all non-air-conditioning appliances and equipment under non-fluctuating part with cities instead of individual technologies as references for achievable energy efficiency.

In the top-down linear model, without the consideration of policy impact, the results of electricity consumption only reflect the changes of socioeconomic and climate drivers. In the overall growth trend, SSP5 shows continuous growth, SSP1 and SSP2 shows first growth and then stable, and SSP3 shows first growth and then decline, which can reflect different social development under different SSP scenarios. However, the linear model cannot reflect the influence of policy factors on different paths. Taking SSP1 as an example, the concept of this pathway focuses on sustainable development, but this cannot be reflected in the socioeconomic data. Under the linear model, the electricity consumption of SSP1 still reaches 431.3 TW h (5629 kW h per capita) in 2050, because of its rapid socioeconomic development without taking into the measures of energy-saving solutions.

Therefore, under the matching policy of different SSPs, the results of the policy model are more reasonable. Except for the continuous growth trend of SSP5, other scenarios show the trend of growth-plateau-decline. In 2100, the electricity consumption of policy models will be 107.7 TW h (2612 kW h per capita) for SSP1, 167.3 TW h per year (4045 kW h per capita) for SSP2, 227.3 TW h per year (4564 kW h per capita) for SSP3, and 729.1 TW h per year (14,647 kW h per capita) for SSP5. In all scenarios, the non-fluctuating part of commercial sector accounts for the largest proportion of electricity consumption. This is aligned with van Ruijven et al. (2019) on a global scale that shows the commercial sector being the dominant driver of energy demand increases, accounting for about 80%. The high SSP5 electricity consumption is mainly contributed by the growing non-fluctuating part of commercial sector, non-fluctuating part of urban residential sector, and the fluctuating part of cooling sector, accounting for 66%, 16.3% and 12.8% respectively in 2100. In terms of fluctuating part, in 2100, the electricity consumption of the fluctuating part of cooling sector is 2.5−11.2 times that of heating sector, which can be explained that the demand for cooling in warmer climate is greater than that for heating. As for non-fluctuating part, the fast-growing non-fluctuating part of commercial and urban residential sector are related to linear correlations to commercial sector GDP and overall GDP × urbanization rate, respectively, and the rapid growth of GDP under SSP5. From a bottom-up perspective, this high level of consumption may only be possible with exploding expansion of information & communication technology and associated use of electricity, such as for data centres and data networks, discussed briefly by Jones (2018).

The energy saving potential is huge. If Jiangsu province takes the road of SSP1 instead of SSP2, SSP3, or SSP5, by 2100, it will save 59.6, 119.6, or 621.4 TW h per year of electricity respectively, accounting for 55%, 111%, or 577% of SSP1 consumption. Compared to Levesque et al. (2018) at global scale, the final energy consumptions in SSP2, SSP3, and SSP5 scenarios are about 1.4, 1.3, and 2.2 times above the SSP1 level by 2100. This suggests that our estimate for SSP2 may be tighter while our estimate for SSP5 may be higher than the global average. The lower difference between SSP1 and SSP2 in Jiangsu, as compared to the global average, may be partly because Jiangsu is relatively developed, limiting the saving potential from new buildings. Choosing Zhenjiang, the city with second best building energy efficiency in Jiangsu, as the basis for non-fluctuating part in SSP2, may be the other reason.

Fig. 5 shows the range of residential and commercial electricity consumption per month, with its maximum and minimum values. The prediction of the minimum and maximum values is the necessary condition for the power bureau to set up the appropriate power supply. By 2100, the minimum of monthly electricity consumption is 6.1−52.3 TW h and the maximum is 15.4−129.1 TW h. The minimum reflects the non-fluctuating part, and the gap between the maximum and minimum indicates the peak of highest monthly air-conditioner electricity consumption each year.

The minimum in SSP1&SSP2 in the policy model is significantly lower than that in the linear model, since the linear models do not take into account the technology improvement and the saturation of appliance usage with GDP growth. As the non-fluctuating part of SSP3&SSP5 of the policy model is also based on linear correlation, they are quite close to the results from the linear model.

As for the maximum, many relevant researches have been carried out, because accurate projection can help to improve the security and stability of the power system and reduce the cost of power generation (Franco and Sanstad, 2007; Auffhammer et al., 2017). By 2100, the lowest monthly value is SSP1 under the policy model, 15.4 TW h, and the highest value is SSP5 under the linear model, 129.1 TW h. It is clear that, from the perspective of policy model, the maximum value follows the order of SSP1 < SSP2 < SSP3 < SSP5, which is the same as the order of temperature rising trend. This may be due to the increase of CDD, which leads to the continuous growth of air-conditioning electricity consumption for cooling.

A more careful inspection over the ratio between the maximum and minimum (see Appendix Fig. A2) will provide information about the required power-generation capacity for seasonal adjustment. In general, the max/min ratio will gradually increase from about 2 ± 0.3 before 2020, to about 2.4 ± 0.4 in 2090−2100 due to warmer climate (except SSP5 in policy model due to its large minimum). For the same reason, this ratio follows the same order of SSP1 < SSP 2 < SSP 3 < SSP5, with another exception of SSP1 in policy model which is roughly the same to SSP2 in policy model, due to the lower minimum in SSP1. In other words, a warmer climate will not only require a larger capacity of power generation, it will require a larger capacity for seasonal adjustment, which will likely add to additional cost per unit of electricity generated, unless the seasonal adjustment comes from renewable that naturally generate more power during summer, such as photovoltaic. It has to note that the incremental of such ratio in this study may be underestimated since our analysis is based on monthly CDD, without detailed analysis into the hot extreme temperature which will determine the maximal power demand.

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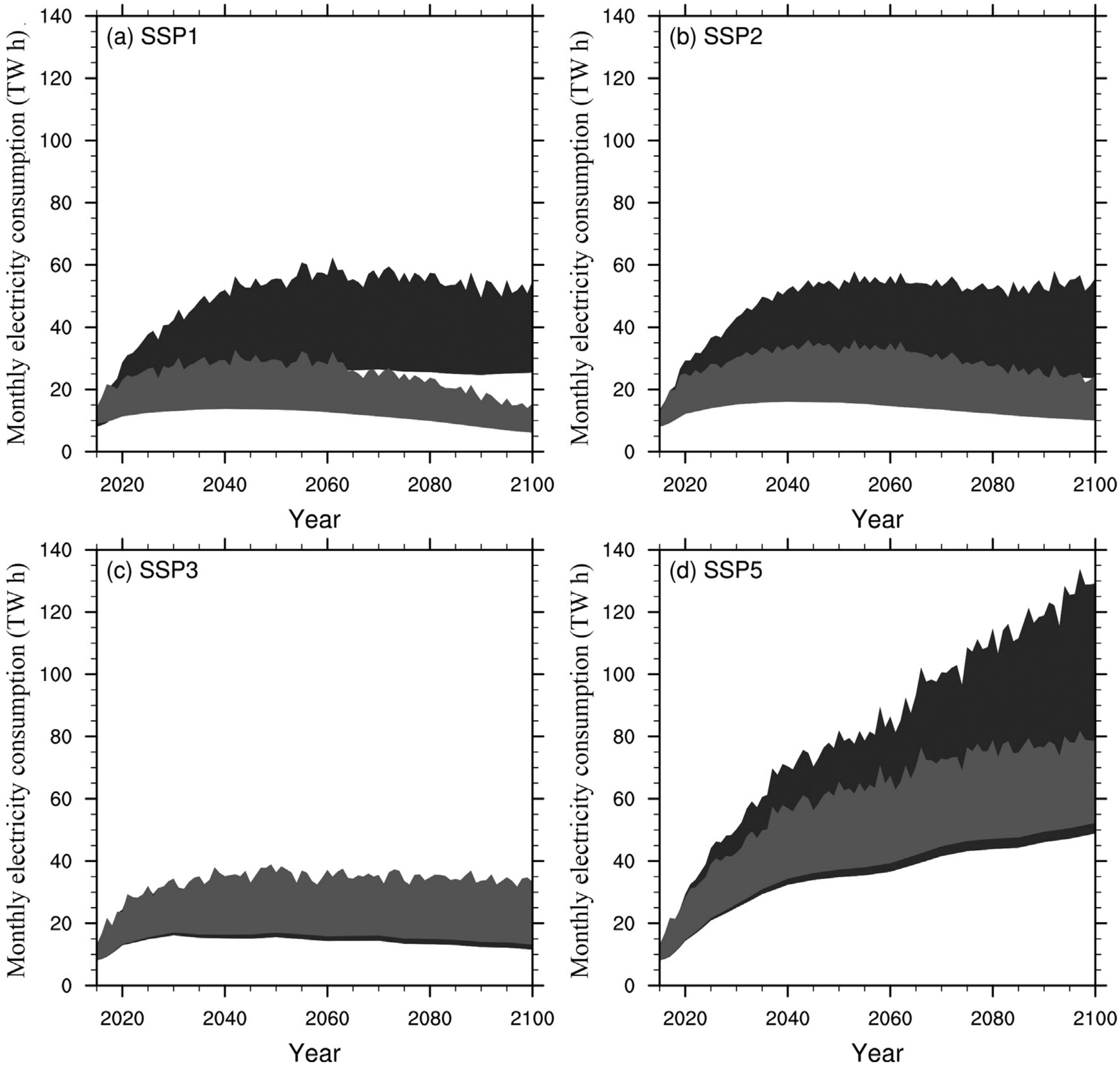

Fig. 5. Maximal and minimal monthly electricity consumption of linear model (dark) and the policy model (grey) in 2015−2100.

4. Conclusion

We construct linear and policy models for the projection of residential and commercial electricity consumption in Jiangsu province until 2100 under various SSP scenarios. In the linear model, only climate and socioeconomic factors are considered, and a top-down approach is adopted; while the policy model is optimized on the basis of the linear model, that is, we also consider the policy factors according to the energy consumption scenarios of prefecture-level cities, and adopt both top-down and bottom-up approach.

In the construction of the two models, we find that the CDD coefficient is about 3 three times that of HDD. In the future, except for SSP1, with the increase of temperature, other scenarios show the trend of CDD growth and HDD decline. Not surprisingly, in 2100, the electricity consumption of the fluctuating part of cooling sector is about 2.5−11.2 times that of heating sector, which means that the cooling demand of air conditioning is far greater than that of heating, and the gap may be even greater in the future. This is also the reason why some prediction results of electricity consumption fluctuation become more intense.

In 2100, the annual mean temperature is 17.4−21.7 °C, the annual electricity consumption is 107.7−937.9 TW h, and the monthly maximum electricity consumption is 15.4−129.1 TW h. Among them, the lowest value belongs to SSP1 and the highest value belongs to SSP5.

The factors considered in the construction of the policy model are more comprehensive than the linear model. In the policy model with bottom-up approach and considering technology progress and policy impact, the projection results are generally lower than the linear model with only top-down approach. Compared with the linear model, under the scenarios of SSP1 and SSP2 in 2100, the annual electricity savings under the policy model are 320 TW h per year and 241.6 TW h per year, respectively. Based on the assumptions of the policy model, the SSPs scenarios are feasible and have huge energy saving potential. Hence, this work can provide support for policymakers to establish energy intensity reduction targets. Due to the similar climatic zone and economic conditions, the results can be extended to other areas of the Yangtze River Delta.

Declaration of Competing Interest

We declare that we do not have any commercial or associative interest that represents a conflict of interest in connection with the work submitted.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.accre.2020.06.005.

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