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Full length article

China's energy-related carbon emissions projections for the shared socioeconomic pathways

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ABSTRACT

意义

The carbon emissions from China's energy consumption are substantially increasing. In this context, it is necessary to predict the long-term dynamics of China's carbon emissions.

GAP

Existing research has investigated future scenarios for China's carbon emissions, but there is still no consensus on such issues as the amount of emissions at peak points and the future carbon emissions path over a longer period.

目的

This paper aimed to explore the dynamics of China's carbon emissions under five Shared Socioeconomic Pathways scenarios (SSP1–SSP5), and to provide further evidences for the comprehensive analysis and prediction of climate change.

过程

Before forecasting the socioeconomic data, an in-sample and out-of-sample approach was used to evaluate the prediction accuracy of the feasible generalized least squares (FGLS) model. By using historical data from 30 provinces, the relationship among population, educational attainment, per capita GDP, and carbon emissions was investigated. Finally, carbon emissions from 2018 to 2100 were predicted based on the settings of different SSP scenarios and model parameters.

结果

The results showed that the peak value was 2030 for SSP1 and SSP5, 2029 for SSP2 and SSP4, and 2028 for SSP3. China will reach the largest cumulative carbon emissions amounting to 814.84 billion tons under the SSP5 scenario. Under all the SSP scenarios, the western region was always the first to reach its peak value, followed by the central region and then the eastern coastal zone. From 2018 to 2100, Jiangsu, Shandong, Guangdong, Zhejiang, Henan, Inner Mongolia, Xinjiang, Hebei, Hubei and Sichuan will contribute significantly to total carbon emissions under different SSP scenarios.

启示

All the results and conclusions would provide significant contributions for carbon reduction and climate change mitigation.

1. Introduction

In recent years, climate change from greenhouse gases such as CO_2 has become a global environmental problem. The fossil fuel demand from human activities is increasing, driven by a dramatic increase in the global population and the on-going acceleration of industrialization in developing nations (O'Neill et al., 2010). The emissions from the resulting greenhouse gases such as CO_2 have also grown, at a speed of 3.4% each year (Wachsmuth et al., 2016), reaching an unprecedented level (Yin et al., 2015). Since reform and opening up, China has entered a period of rapid development and energy has become the foundation of China's development (Wang and Chen, 2018). Owing to the limitations of energy use efficiency and clean technology, rapid development tends to continuously increase energy consumption, bringing serious challenges for environmental protection and climate change (Lv and Xu, 2019; Nathaniel and Iheonu, 2019). In 2009, China became the biggest emitter of greenhouse gas emissions (Wang et al., 2019). The carbon emissions in China in 2017 accounted for around one third of the global carbon emissions (British Petroleum, 2018). Against this background, China must take responsibility as an important contributor to act to reduce global carbon emissions. 研究背景

The Chinese government has adopted a range of emissions mitigation measures to cope with global climate change. For instance, at the 2009 Copenhagen Climate Change Conference, various nations reached a basic consensus on emissions mitigation. China was the first developing nation to propose its target for energy conservation and emissions reduction. The Chinese government has promised that in 2020 carbon intensity will be reduced to 55% to 60% of the level in 2005 (Guan et al.,

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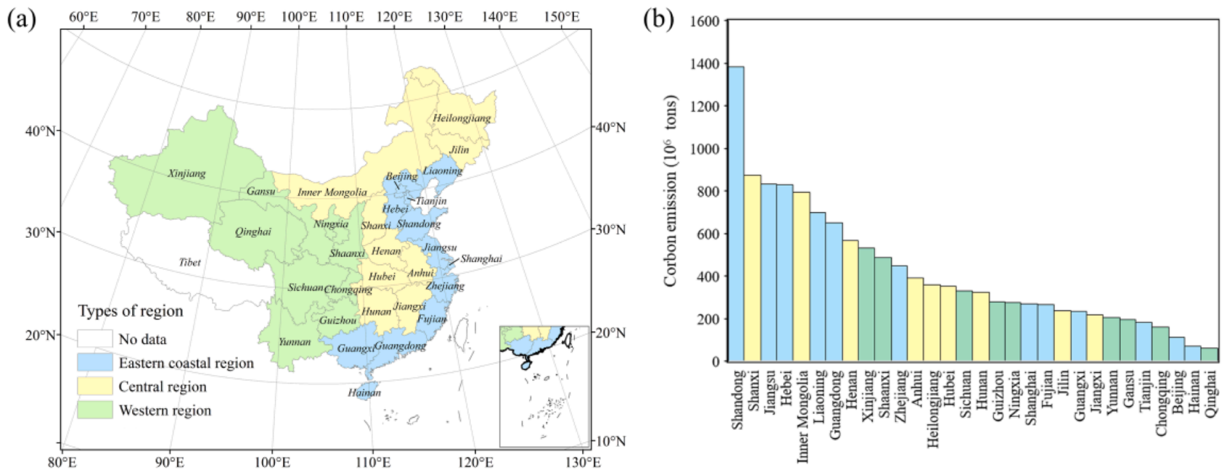

Fig. 1. Geographical location and carbon emissions of 31 provinces in China (no emissions data from Tibet), 2017.

2014). At the 2015 Paris Climate Change Conference, based on the Intended Nationally Determined Contributions (INDC), China promised to reach its peak in carbon emissions by around 2030 (UNFCCC, 2015; Semieniuk and Yakovenko, 2020). The Integrated Work Plan on Energy Conservation and Emission Reduction issued by the State Council (2016–2020) clearly demands that the energy use efficiency should be improved so that energy consumption per RMB 10000 of GDP can be reduced by 15% compared with 2015.

The emissions reduction measures adopted by China have already produced significant effects, while industrialization and urbanization have still maintained rapid development (Yu et al., 2017). In order to explore whether China can meet its commitment to reduce carbon emissions and whether it is possible to peak carbon emissions as soon as possible, it is necessary to make reasonable predictions about the long-term dynamics of carbon emissions. Research has focused on whether the peak value targets can be accomplished. For instance, some people have claimed that the peak value year for China's carbon emissions was realized before 2015 (Guan et al., 2018). Other researchers in China believe that the peak value may be reached between 2020 and 2025 (Yu et al., 2018), 2025 and 2030 (Song et al., 2018), or in 2030 (Gallagher et al., 2019). Specifically, Chen (2017) designed an energy supply and demand model for China and two corresponding future scenarios, showing that China's carbon emissions will peak in 2025. Based on an Integrated Model of Economy and Climate (IMEC), Mi et al. (2017) predicted that the peak of carbon emissions in China may occur in 2026. Fang et al. (2019) developed an extended set of STIRPATs by Regression on Population, Affluence, and Technology to predict carbon emissions, showing that China's carbon emissions peak is between 2028 and 2040, with 2030 the best peak year. However, many still believe that China's commitment is too ambitious and the peak value for carbon emissions will be delayed (Zhou et al., 2013; Yuan et al., 2014; British Petroleum, 2016; Elzen et al., 2016; Xu et al., 2019; Qi et al., 2020).

意义

In summary, the results of research into the peak value of carbon emissions in China are often conflicting. There is still no consensus on such issues as the amount of emissions at peak points and the future carbon emissions path over a longer period. Notably, owing to the existence of aggregation bias, analysis based on national data can easily ignore the variations caused by regional heterogeneity (Herrerias et al., 2013; Xu, 2018). Given the impact from society, the economy, and policies, and difference in the emissions pathways among regions, the emissions track for China as a whole is not necessarily very compatible with the conditions in each province. Therefore, provincial-level estimation of China's emissions track may reduce the overall uncertainty, so the results can be more precise and reliable. These research directions not only have national significance, but also can enhance the feasibility of regional energy conservation policies in the future.

GAP

It is estimated that China's future carbon emissions scenario is a macro and complicated problem and its analysis path should include the three levels of society, the economy, and policies. Existing studies rarely take into account climate policy implementation and the resulting uncertainty about future socioeconomic development, which makes the prediction of carbon emissions challenging. This paper uses Shared Socioeconomic Pathways (SSP) to contribute to this debate (Hegre et al., 2016; O'Neill et al., 2017). In 2010, the IPCC adjusted their scenario development model and proposed a set of new frameworks consisting of social economic scenarios and climate scenarios (Moss et al., 2010). The social economic scenarios are expressed with various SSP. The IPCC designed five types of social and economic development paths to predict the possible results on different climate policies: SSP1 is the sustainable path, SSP2 is the intermediate path, SSP3 is the regional competition path, SSP4 is the imbalanced path, and SSP5 is the development path dominated by fossil fuels (Riahi et al., 2017). SSPs is a multilateral system, among which population, per capita GDP, and education attainment are three key variables (Böhmelt, 2017). In terms of policy support for climate change, the effects, fragility, adaptation, and mitigation analysis under the SSP will be gradually applied to different nations and regions and to research on climate change science in different industry sectors (Chen et al., 2019; Huang et al., 2019).

GAP

多方面的

The contributions made by this article can be summarized into two aspects: (1) We proposed a type of new carbon emissions impact index portfolio, making use of "in-sample" and "out-of-sample" approaches to test the predictability of the model. (2) Based on the different settings of SSP, a multi-scenario analysis was conducted on the carbon emissions in various regions from such perspectives as historical trends and future predictions. The results can help the Chinese government properly adjust the current development mode and formulate scientific carbon emissions-reduction policies in line with local conditions.

The organizational structure of the remainder of this paper is: Section 2 offers an overview of the research area. Section 3 introduces the selected variables, models and data sources. Section 4 includes model identification and future predictions and presents the carbon emissions results from 2018 to 2100 under the five types of SSP scenarios. Section 5 contains the discussion and policy suggestions based on the predicted results.

2. Study area

In 2017, China had a population of 1390.08 million, with GDP up to 13.17 trillion US dollars. In recent years, China's energy consumption has been huge. The total energy consumption of China was equivalent to 4.49 billion tons of standard coal in 2017. The consumption of raw coal, crude oil and natural gas accounted for 86.2%, generating a large

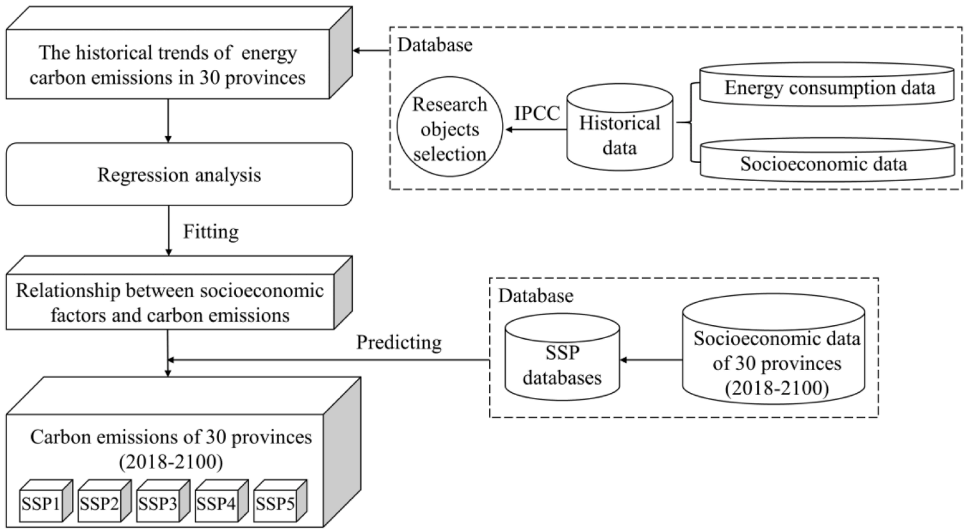

Fig. 2. Flowchart of carbon emissions projections.

volume of energy carbon emissions, which has brought severe challenges for the environment. Therefore, predicting China's energy carbon emissions and the regional emissions in the future is of great significance in formulating targeted emissions reduction policies.

China is divided into 31 provinces. The geographical location and energy carbon emissions of each province is marked in Fig. 1. Due to the lack of energy consumption data for Tibet, this paper focused on the remaining 30 provinces. Based on the level of economic development and geographical location, all provinces were classified into the three economic zones of the eastern coastal region, central region, and western region. In 2017, the eastern coastal region, central region and western region contributed 47.39%, 32.64% and 19.97% of energy carbon emissions, respectively.

3. Methods

3.1. Research framework

In this paper, we considered that the total population, educational attainment, and per capita GDP were the main socioeconomic factors that affected carbon emissions. First, all else being equal, a larger population size usually leads to more carbon emissions (Yang et al., 2015; Qi and Li, 2020). The population data for each province beyond 2017 are based on a multidimensional population model. Second, we used the population with a tertiary education to represent the education level. Educational attainment can not only capture the quality of human development, but also is a proxy for the advanced nature of technology in regions (Jänicke, 2008; Bernauer and Böhmelt, 2013; Böhmelt, 2017). Related to this is, third, per capita GDP, which is an effective predictor of carbon emissions (Zhang and Zhang, 2018; Akalpler and Hove, 2019; Sheng et al., 2020). In this paper, economic data beyond 2017 were calculated based on the Cobb-Douglas production model. The per capita GDP was defined as the ratio of GDP to population. To verify our assumptions, we first calculated the carbon emissions using the energy consumption data for 30 provinces in China from 1989 to 2017. After obtaining the complete dataset, regression analysis was used to quantify the relationship between the above three factors and carbon emissions. Based on the scenario settings for different SSP, we forecasted the data of the above three factors from 2018 to 2100. Finally, the model parameters and explanatory variables were used to predict carbon emissions from 2018 to 2100. The research framework is shown in Fig. 2.

3.2. Explained variable: carbon emissions (CE)

In this paper, energy carbon emissions were based on the sectoral consumption of different fuels, following previous studies (Zhang et al., 2020), as shown in Eq. (1) below:

$$CE_{energy} = \sum_{i=1}^{8} CE_i = \sum_{i=1}^{8} M_i \times RCO_i \times CC_i \times \times LCV_i \times \frac{44}{12} \tag{1}$$

where CE_{energy} are the energy-related carbon emissions, M denotes the amount of specific energy consumption, RCO denotes the rate of carbon oxidation, CC denotes the carbon content, LCV denotes the low calorific value. For the carbon emissions coefficients of the eight fossil fuels, see Zhang et al. (2020).

3.3. Model for carbon emissions

In addition to the three substantive 实质性的 predictors listed above that were relevant to SSP, we also included an annual trend. Moreover, we considered the quadratic term of per capita GDP based on the discussion on the EKC (Ulucak and Bilgili, 2018; Leal and Marques, 2020). The substantive variables in this paper were all log transformed. Eq. (2) is the model that was used for the predictions.

Table 1.
Overview of SSPs' China's characteristics.

	TFP growth	TFP convergence	Fertility rate	Mortality rate	Migration	Education attainment
SSP1	Medium	High	Low	Low	Medium	Rapid
SSP2	Medium	Medium	Medium	Medium	Medium	Global trend
SSP3	Low	Low	High	High	Low	Constant enrollment rate
SSP4	Medium	Low	Low	Medium	Medium	Constant enrollment rate
SSP5	High	High	Low	Low	High	Rapid

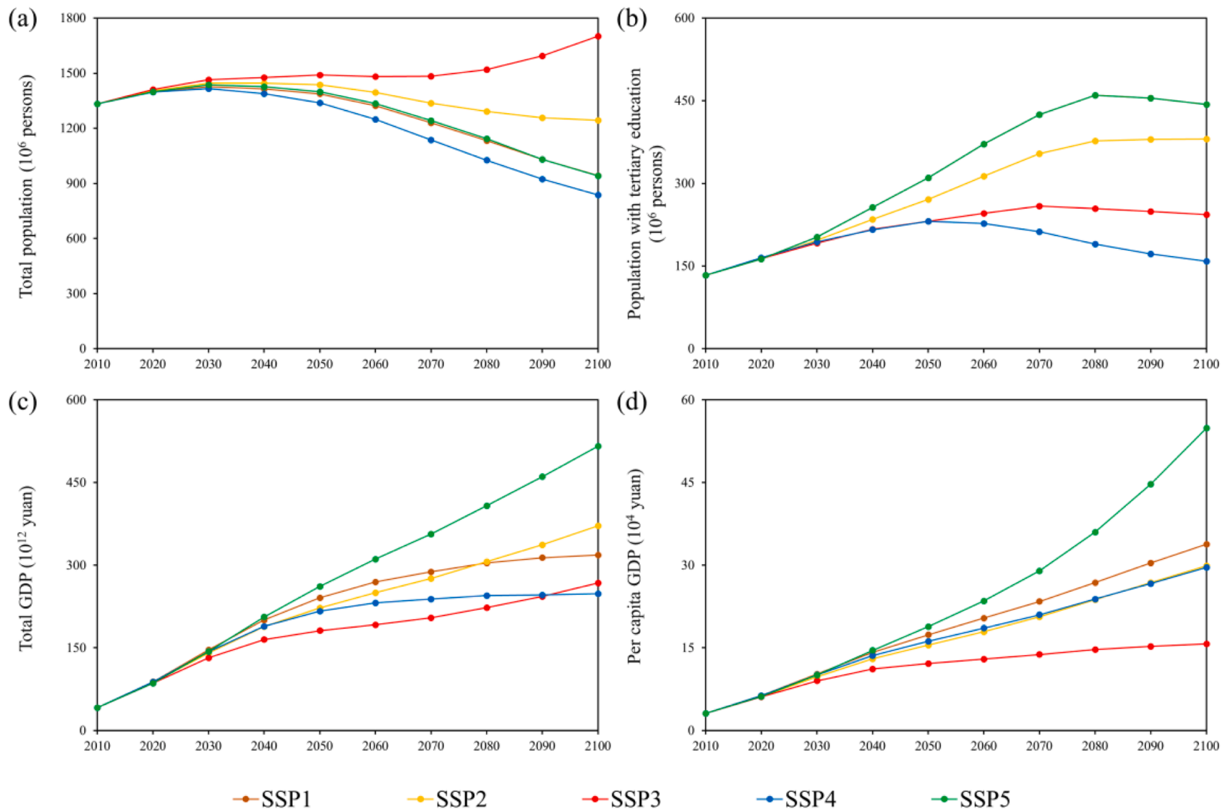

Fig. 3. The trend for GDP and population under SSP1–SSP5 scenarios.

$$\ln CE_{it} = \alpha + \beta_1 \ln GDP_{it} + \beta_2 (\ln GDP_{it})^2 + \beta_3 \ln POP_{it} + \beta_4 \ln EDU_{it} + \beta_5 Year_{it} + \varepsilon_{it} \quad (2)$$

where *CE* denotes carbon emissions, *GDP* denotes per capita GDP, *POP* denotes population, *EDU* denotes education attainment, and *Year* denotes the year-trend variable. In Eq. (2), α denotes the constant, $\beta_1 \sim \beta_5$ denote the regression coefficients, and ε denotes the random error term.

3.4. Data preparation

The basic data (energy consumption data, economic data and population data) used by the model were obtained from the *China Statistical Yearbook* and *National Energy Statistics Yearbook*.

Population and GDP for 30 provinces from 2018 to 2100 under SSP1–SSP5 scenarios were based on a multidimensional population model and Cobb-Douglas production model. Using historical data and different scenario settings (Table 1), this paper predicted three substantive explanatory variables. Considering the earliest years available from the data related to energy consumption in various regions, we obtained the information from 1989 to 2017 on these variables and this formed the basic data for the panel regression model. Therefore, the effects of adaptation and mitigation scenarios included in different SSP only emerged after the year 2017. Fig. 3 shows the prediction results of the five SSP scenarios from 2018 to 2100, including the predictions of three variables and the economy aggregated. It should be noted that although it is hard to obtain data on energy consumption in Tibet, this does not affect the forecast of these three variables. Thus, the results of Fig. 3 are the overall data for 31 provinces including Tibet.

Table 2.
Baseline models for carbon emissions (ln), 1989–2003.

Models	OLS (1)	FE (2)	RE (3)	FGLS (4)
Per capita GDP (ln)	1.121**	1.404***	1.287***	1.004***
	(0.544)	(0.269)	(0.266)	(0.329)
Per capita GDP^2 (ln)	−0.054*	−0.042***	−0.036**	−0.027
	(0.032)	(0.016)	(0.016)	(0.021)
Population (ln)	0.354***	1.396***	0.797***	0.694***
	(0.053)	(0.365)	(0.096)	(0.013)
Education (ln)	0.602***	0.057	0.070*	0.041***
	(0.058)	(0.040)	(0.039)	(0.010)
Year Trend	−0.023**	−0.049***	−0.041***	−0.014**
	(0.009)	(0.013)	(0.011)	(0.006)
Constant	40.16**	81.14***	72.11***	19.31*
	(17.77)	(23.79)	(21.12)	(11.13)
Observations	450	450	450	450
F test	68.24***			
Hausman test	26.71***			
Wooldridge test	85.96***			
Heteroscedasticity test	8028.18***			
Friedman test	55.51***			

Note:
*** represents the significance at the one percent level;
** represents the significance at the five percent level;
* represents the significance at the ten percent level.

4. Model recognition and results

4.1. In-sample approach

To assess the above-mentioned hypothesis, we first adopted models to estimate the data from 1989 to 2003. Model (1) is a mixed least squares model. Model (2) in Table 2 is a fixed effects model and Model (3) is a random effects model. The F-test value of Model (2) 68.24 and it passed the 1% significance test, indicating that the fixed effects model

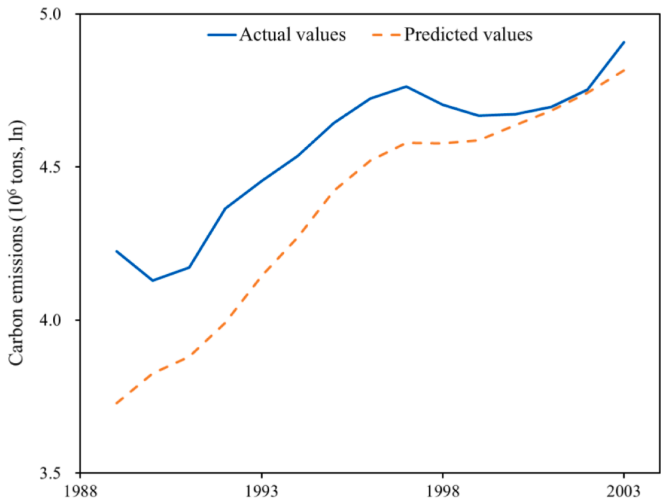

Fig. 4. Median levels of carbon emissions (ln), 1989–2003.

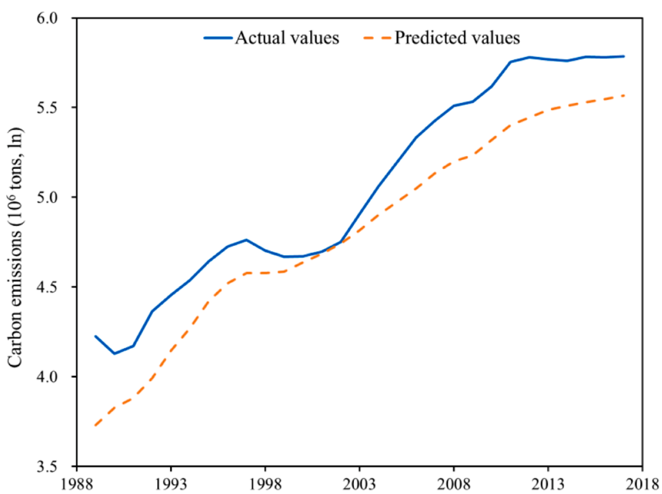

Fig. 5. Median levels of carbon emissions (ln), 1989–2017.

was better than mixed effects model. The Hausman test value was 26.71 and also passed the 1% significance test, implying that the fixed effects model was more appropriate for the panel data in this paper than the random effects model. Through a heteroscedasticity test, Wooldridge test, and Friedman test, we conducted an assessment with the feasible generalized least squares (FGLS) method or Model (4). Table 2 summarizes the results of the basic models. Most variables conformed to expectation and had statistical significance. The quadratic term of per capita GDP was the only exception as it did not reach the normal level of significance.

Then, we calculated the estimated value of Model (4) in this time period and used the median of carbon emissions to compare the model estimated value with the real value. Model (4) could relatively accurately predict carbon emissions even if the carbon emissions had always been underestimated compared with the real amount (Fig. 4). Finally, we used MAPE (the mean absolute percentage error) to measure and predict the precision with a result of 0.119, which fell within the scope of a good forecast (Pao and Tsai, 2011), which means that the prediction was "off" by about 12%.

4.2. Out-of-sample approach

The intent here was to explore whether the methods in Model (4) could maintain precision in the forecast of carbon emissions in face of new data. Like Fig. 4 above, we drew a graph to describe the estimated value and real value of the median carbon emissions (Fig. 5). The difference between Figs. 5 and 4 is that the former extends the forecast to the year 2017. Results showed that MAPE under this condition was 0.067, which falls within the scope of a highly accurate forecast (Pao and Tsai, 2011). Of course, it should be acknowledged that uncertainties still exist in the model forecast results, but the fact that its forecast of new data was more accurate than that of the in-sample data was reassuring.

Table 3.
Baseline models for carbon emissions (ln), 1989–2017.

Models	OLS (1)	FE (2)	RE (3)	FGLS (4)
Per capita GDP (ln)	0.878***	2.162***	1.021***	0.992***
	(0.218)	(0.037)	(0.125)	(0.130)
Per capita GDP^2 (ln)	−0.037***	−0.089***	−0.019***	−0.016**
	(0.012)	(0.002)	(0.007)	(0.007)
Population (ln)	0.408***	0.354***	0.609***	0.492***
	(0.044)	(0.004)	(0.087)	(0.147)
Education (ln)	0.457***	0.032***	0.147***	0.144***
	(0.049)	(0.002)	(0.038)	(0.039)
Year Trend	0.002	−0.013***	−0.034***	−0.037***
	(0.005)	(0.001)	(0.008)	(0.009)
Constant	−9.503	15.61***	59.90***	66.52***
	(10.00)	(1.76)	(16.02)	(17.53)
Observations	870	870	870	870
F test	71.56***			
Hausman test	11.44**			
Wooldridge test	114.86***			
Heteroscedasticity test	5286.06***			
Friedman test	132.14***			

Note:
*** represents the significance at the one percent level;
** represents the significance at the five percent level.

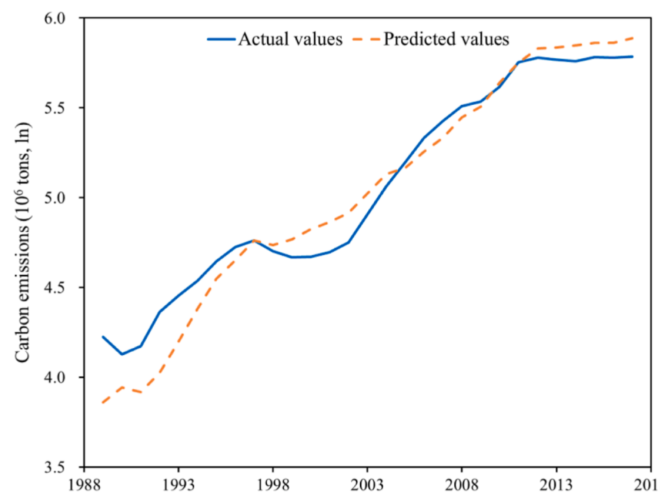

Fig. 6. Median levels of carbon emissions (ln), 1989–2017.

Therefore, based on the above analysis, we demonstrated that the forecast of carbon emissions from 2018 to 2100 is feasible. The following forecasts were all conducted with the methods of Model (4), but with some improvements: we extended the years of basic data of the model from 1989 to 2017, hence obtaining the Model (4) results for Table 3. Compared with Table 2, the quadratic term of the per capita GDP was significant at the level of 5%, which was consistent with other research results (Lindmark, 2002; Jalil and Mahmud, 2009; Acaravci and Ozturk, 2010). In other words, per capita GDP had an inverted U-shaped relationship with carbon emissions. Fig. 6 shows the final fitted result.

With the help of the model parameters and the forecast data on explanatory variables, we predicted the carbon emissions under

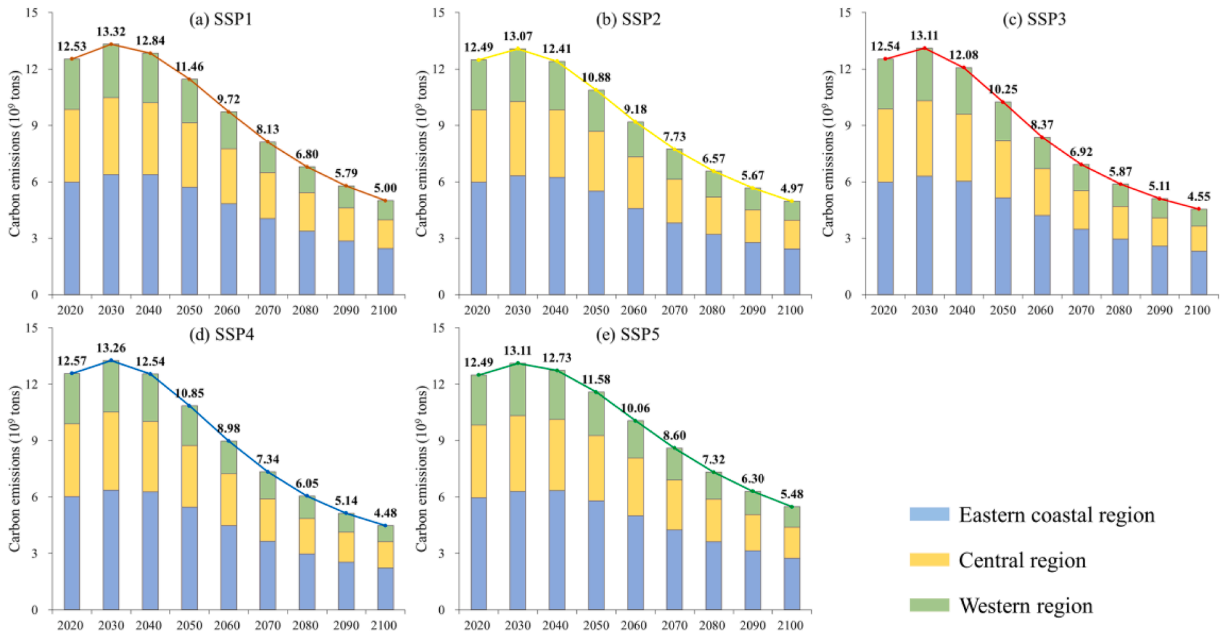

Fig. 7. The trend of carbon emissions under different scenarios.

Table 4
Cumulative total carbon emissions from 2018 (Unit: 10^9 tons).

Year	SSP1	SSP2	SSP3	SSP4	SSP5
2020	37.61	37.61	37.63	37.77	37.45
2030	168.43	167.69	167.60	169.48	166.78
2040	299.28	296.13	293.03	299.27	296.01
2050	419.22	411.67	402.24	414.84	416.36
2060	531.96	519.05	500.32	520.51	532.11
2070	609.21	592.87	566.22	591.38	613.34
2080	681.66	662.99	628.39	656.84	690.92
2090	742.87	723.18	681.96	711.88	757.35
2100	795.44	775.60	729.26	754.24	814.84

SSP1–SSP5 scenarios from 2018 to 2100, constituting the final forecast.

4.3. Total carbon emissions in SSP1–SSP5 scenarios

A comparison of the total carbon emissions under five SSP scenarios showed that their changing trends were similar (Fig. 7). Notably, the forecast peak values under the five scenarios were all between 2025 and 2030. The peak value was 2030 for SSP1 and SSP5, 2029 for SSP2 and SSP4, and 2028 for SSP3. In terms of time range, this was basically consistent with recent estimations (Li et al., 2018; Yu et al., 2018). It's worth noting that projections released by United Nations (2011) show that China's population peaks in 2027. Energy supplies will not be able to meet the needs of a growing population until 2025. In other words, China's carbon emissions are unlikely to peak before 2025. From this point of view, this paper's prediction is reasonable. The SSP4 scenario had the biggest peak value of 13344.0 million tons, followed by 13325.2 million tons for SSP1 and 13179.5 million tons for SSP2. Carbon emissions peak values under SSP3 and SSP5 scenarios were 13118.6 million tons and 13116.9 million tons, which were close to each other. If the result for 2100 alone was examined, carbon emissions under the SSP5 scenario were the highest, reaching 5409.8 million tons, followed by 4957.2 million tons under the SSP2 scenario. The carbon emissions of SSP1 (4935.8 million tons) and SSP3 (4499.1 million tons), ranked 3rd and 4th, were higher than that of SSP4 (4492.9 million tons).

Moreover, the paper estimated the cumulative amount of carbon emissions from 2018 to 2100 under the five SSP scenarios (Table 4). The cumulative carbon emissions under SSP1–SSP5 scenarios ranged from 729.26 billion tons to 814.84 billion tons. For a long period in the early years of this century, the cumulative carbon emissions under the SSP1 scenario remained the highest. By 2060 at the latest, however, the cumulative carbon emissions under the SSP5 scenario overtook those of the other four scenarios and remained the highest until 2100. The cumulative carbon emissions in China will be 500.32 Gt to 532.11 Gt from 2018 to 2060. In other words, in order to achieve the goal of carbon-sequestration by 2060, China needs to reduce emissions by more than 500 Gt.

In the scenarios of SSP1–SSP5, the three regions witnessed a similar trend in carbon emissions, but the proportions differed sharply (Fig. 7). The carbon emissions in the eastern coastal zone were significantly higher than those of central and western regions. The carbon emissions in these three regions all reached the peak value before 2040. Under each SSP scenario, the western region was always the first to reach its peak value, followed by the central region and then the eastern coastal zone. For example, under the scenario of SSP3, the peak value of the western region occurred in 2025, 4 and 6 years earlier than that of the central region and the eastern coastal zone, respectively. In terms of the contribution of regional carbon emissions under different SSP scenarios to the total carbon emissions, the eastern coastal zone made the major contribution while the other two regions made much lower contributions. For specific regions, carbon emissions reduction also differed under different scenarios. For example, in the western region, the reduction rate and range under the scenarios of SSP3 and SSP4 were very similar compared with the other three scenarios.

4.4. Carbon emissions for 30 provinces in SSP1–SSP5 scenarios

Fig. 8 displays the provincial carbon emissions in each scenario from 2020 to 2100. Looking at SSP2 scenario as an example, Fig. 9 shows the carbon emissions of 30 provinces in 2030, 2050, 2080 and 2100. The results for the other four scenarios are stored in the Appendix section. In 2030, most provinces were still at the stage of carbon emissions increases and this situation changed around 2050. In 2100, the carbon emissions of all provinces had dropped compared with 2017 but with different reduction rates. As for peak value, different provinces had significant heterogeneity under SSP1–SSP5 scenarios, and their contribution to the total carbon emissions in different periods was not the same. For example, Beijing reached carbon emissions peak value in 2026

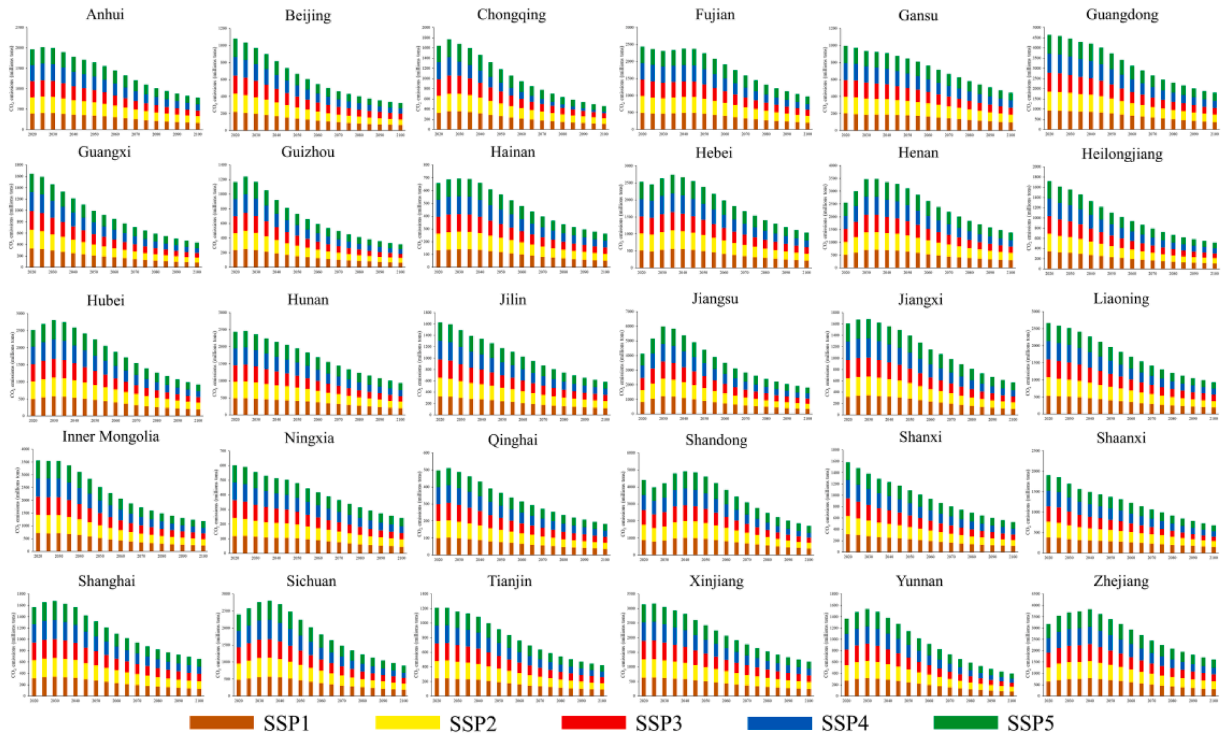

Fig. 8. Carbon emissions of 30 provinces under different scenarios.

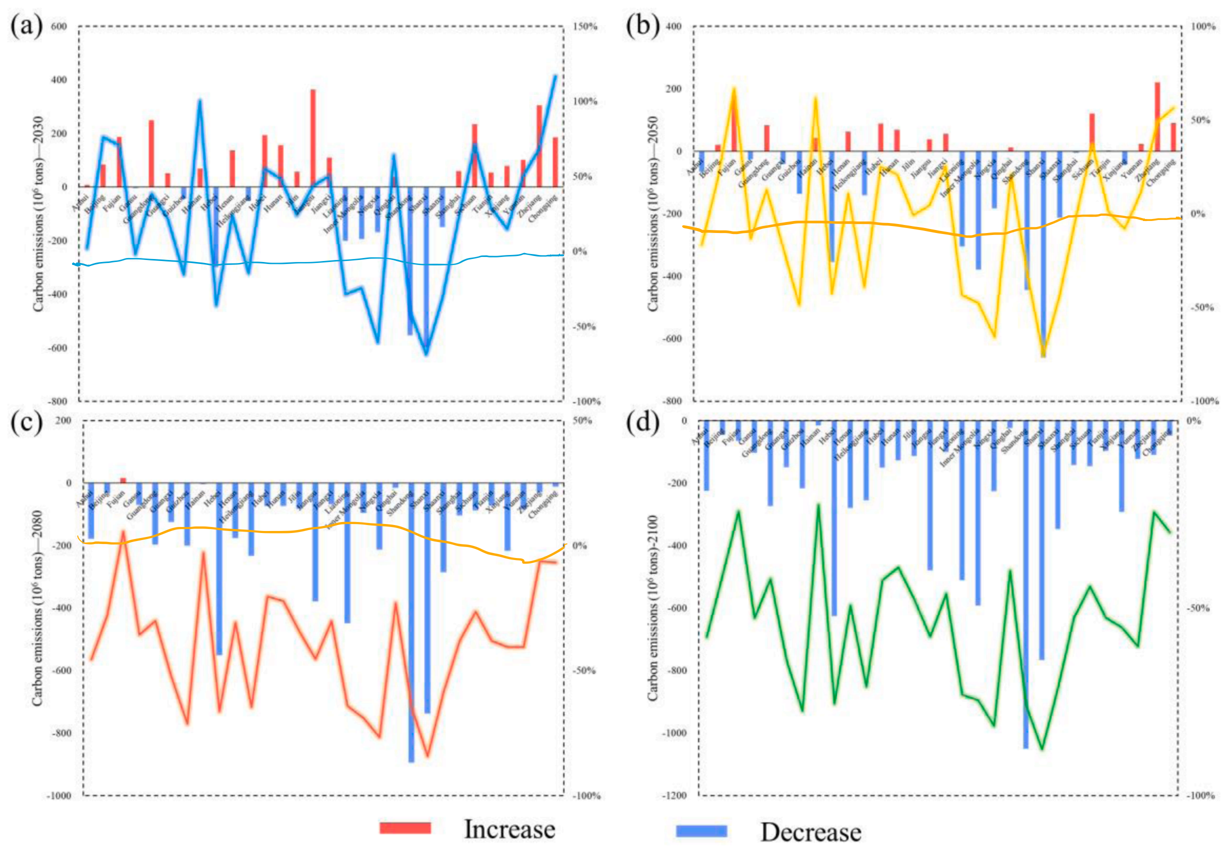

Fig. 9. Changes in carbon emissions compared with 2017 in the SSP2 scenario.

Table 5.
Cumulative total carbon emissions from 2018 to 2100 of 30 provinces (Unit: 10^9 tons).

Province	SSP1	SSP2	SSP3	SSP4	SSP5
Anhui	24.45	23.90	21.85	23.80	24.91
Beijing	10.64	10.36	10.30	10.22	10.55
Chongqing	19.13	18.71	17.51	13.17	19.05
Fujian	31.19	30.79	28.73	29.47	32.37
Gansu	12.89	12.70	11.49	12.21	12.79
Guangdong	56.48	53.41	50.39	53.31	56.27
Guangxi	15.73	15.12	14.89	15.55	16.71
Guizhou	11.76	11.32	10.89	11.37	12.05
Hainan	8.33	8.13	7.75	8.12	8.42
Hebei	33.68	32.68	31.01	32.25	34.60
Henan	42.83	42.90	38.22	40.85	44.31
Heilongjiang	17.51	16.77	16.18	17.04	17.95
Hubei	32.49	32.21	29.11	30.99	33.63
Hunan	29.93	28.75	25.88	27.86	30.31
Jilin	17.99	17.91	16.82	17.40	18.44
Jiangsu	62.32	60.57	59.27	60.48	65.24
Jiangxi	19.68	19.08	18.22	19.46	21.52
Liaoning	29.73	29.53	28.59	28.51	29.76
Inner Mongolia	38.83	38.20	36.68	37.69	39.62
Ningxia	7.17	7.02	6.45	6.95	7.43
Qinghai	5.67	5.52	5.39	5.58	5.76
Shandong	61.84	58.65	53.28	56.09	63.80
Shanxi	16.71	16.30	15.56	16.29	17.30
Shaanxi	21.77	21.21	18.70	20.49	21.59
Shanghai	19.78	19.49	18.94	19.04	19.95
Sichuan	32.01	31.22	29.53	30.29	32.75
Tianjin	13.82	13.67	13.01	13.03	13.66
Xinjiang	36.77	36.41	34.69	35.40	37.04
Yunnan	16.59	16.11	15.05	15.64	17.01
Zhejiang	47.73	46.95	44.86	45.70	50.05

while Shanghai, Sichuan, and Yunnan reached their peak values between 2030 and 2040, implying that these regions' carbon emissions reached saturation relatively early and their contribution to the total carbon emissions dropped after 2040. After the middle of this century, all provinces entered a stage of consecutive reduction in carbon emissions.

Table 5 lists the cumulative total carbon emissions of the 30 provinces under different scenarios from 2018 to 2100. It shows that Jiangsu, Shandong, Guangdong, Zhejiang, Henan, Inner Mongolia, Xinjiang, Hebei, Hubei and Sichuan ranked among the top 10 in cumulative carbon emissions and the sum of carbon emissions in these ten provinces reached 55.81% to 56.12% of the total carbon emissions. Xinjiang, Inner Mongolia, and Hebei have formed an industrial structure dominated by industry and manufacturing. This high-carbon emission industrial structure has become the main reason for a large amount of energy consumption and carbon emissions. For other provinces, the regional population size is the main driving force.

In summary, under different SSP scenarios, the carbon emission paths varied. The total cumulative carbon emission ranged from 729.26 billion tons to 814.84 billion tons, and SSP5 had the largest carbon emissions. The carbon emissions peak value and the time to reach the peak value in different regions were not consistent, leading to differing contributions to total carbon emissions. Therefore, when assessing the carbon emissions of a certain region in the future, we should consider the real social and economic status.

5. Conclusion and discussion

5.1. Main conclusion

To provide a picture of carbon emission development in China, this paper expanded on existing research and forecasted the carbon emissions of 30 provinces from 2018 to 2100. In this process, we used SSP to forecast carbon emissions in China. The results of this paper provide more evidence for the development trends of carbon emissions in China as a whole and in various regions and support relevant research in the future.

The main conclusions of this study can be drawn. (1) The largest cumulative carbon emissions amounting to 814.84 billion tons under the SSP5 scenario. (2) Under the SSP1–SSP5 scenarios, the annual emissions, and cumulative emissions of carbon in the eastern coastal zone were always higher than those of central and western regions. (3) From 2018 to 2100, the provinces with the highest cumulative carbon emissions were Jiangsu, Shandong, Guangdong, Zhejiang, Henan, Inner Mongolia, Xinjiang, Hebei, Hubei and Sichuan under different SSP scenarios. An important finding was that, in the future, the variation in the quantity and rate of carbon emissions in different provinces under different scenarios differed sharply.

5.2. Discussion

For China, the most pressing task now is to set more ambitious climate targets in the 14th Five-Year Plan to reduce coal's share of the total energy to less than 50 percent and accelerate the transformation of the energy structure. A national and local plan of action for reaching the summit and a viable medium- and long-term low-carbon development road map at the economic and technical levels should be developed as soon as possible. In the long run, in order to achieve the above-mentioned goals, China should deepen and accelerate the phase-out of fossil energy power generation, strengthen the development of clean, sustainable and renewable energy, represented by wind and solar power generation, and promote it to become the main body of energy and power systems. China is pushing for capital and technology to gather in the Carbon Capture and Storage (CCS) sector. This facilitates the commercialization and civilization of CCS technology. In addition, it is necessary to consider the status of social and economic development and the specific effects exerted by it when regional carbon emissions are assessed and emission reduction policies are formulated.

There are some limitations to this study. On the one hand, the factors included in the carbon emission forecasting framework in this paper are effective, but the quantity is not rich. In addition, a large part of the parameters required for setting the SSPs scenario in this article are assumptions and manual estimates. This has caused some damage to the accuracy of the scenario analysis. On the other hand, after basically defining China's carbon emission reduction targets, it is necessary to carry out relevant research at the sub-level region, which will be conducive to the achievement of national targets. Due to the limitation of research method and sample size, it is not possible to predict the carbon emission scenario of smaller administrative units. In future studies, we will focus on these two issues with a view to making a long-term contribution to China's development of a sound and effective carbon emission reduction action plan.

Declaration of Competing Interest

The authors declare no conflicts of interest

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Appendix

Fig. A.1, Fig. A.2, Fig. A.3, Fig. A.4

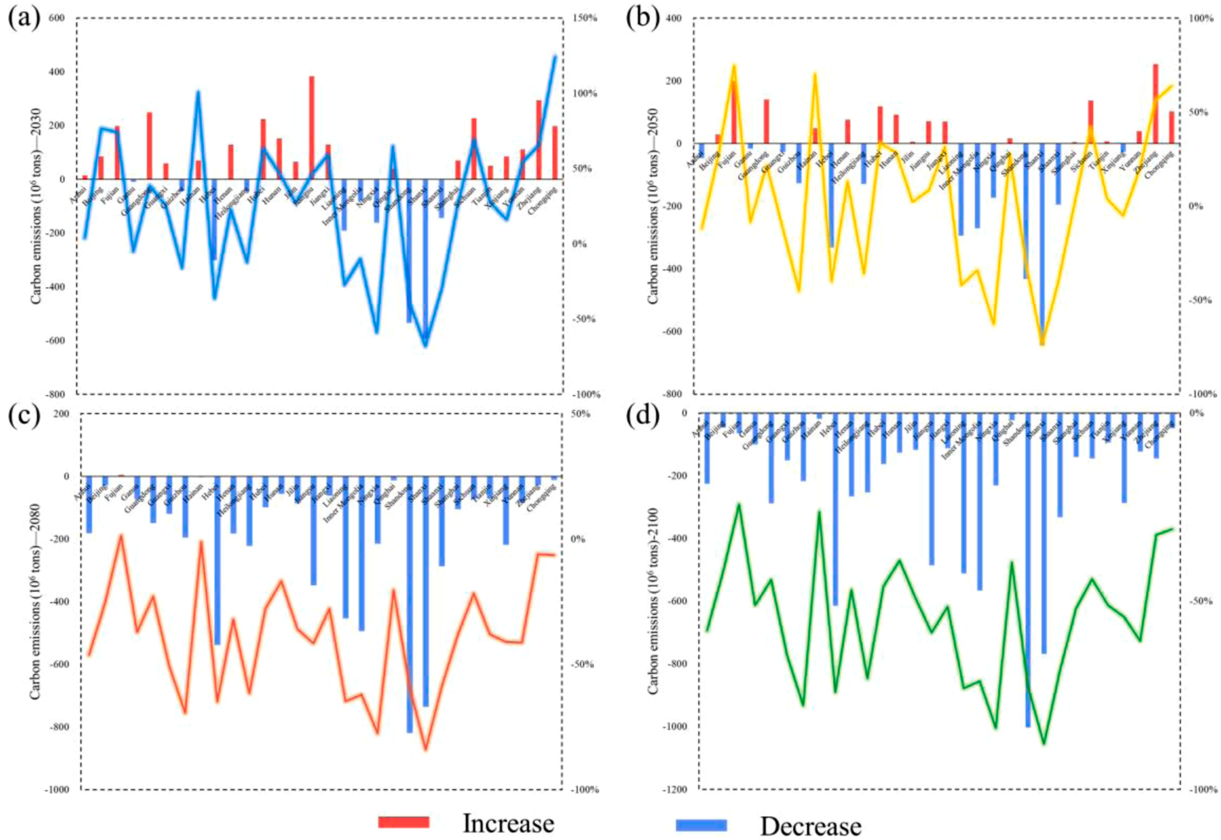

Fig. A.1.. Changes in carbon emissions compared with 2017 in the SSP1 scenario.

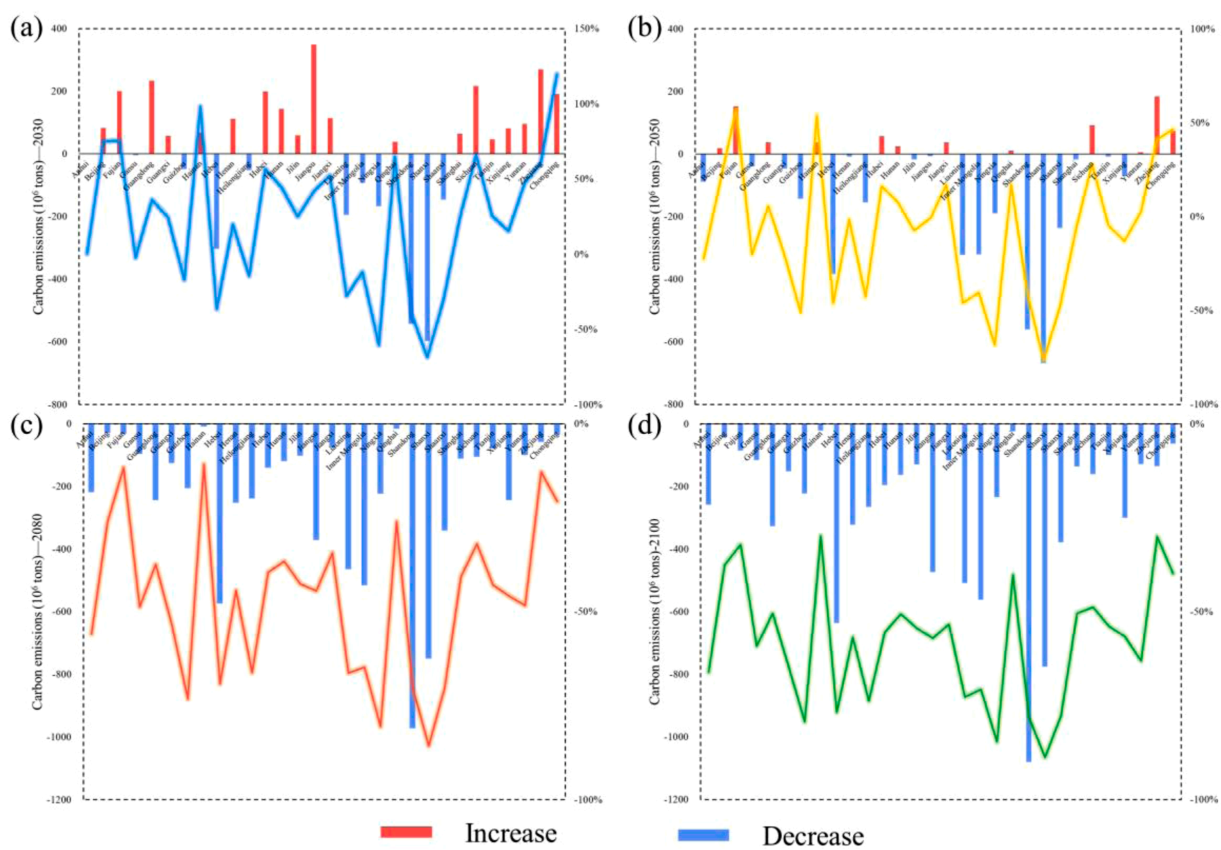

Fig. A.2.. Changes in carbon emissions compared with 2017 in the SSP3 scenario.

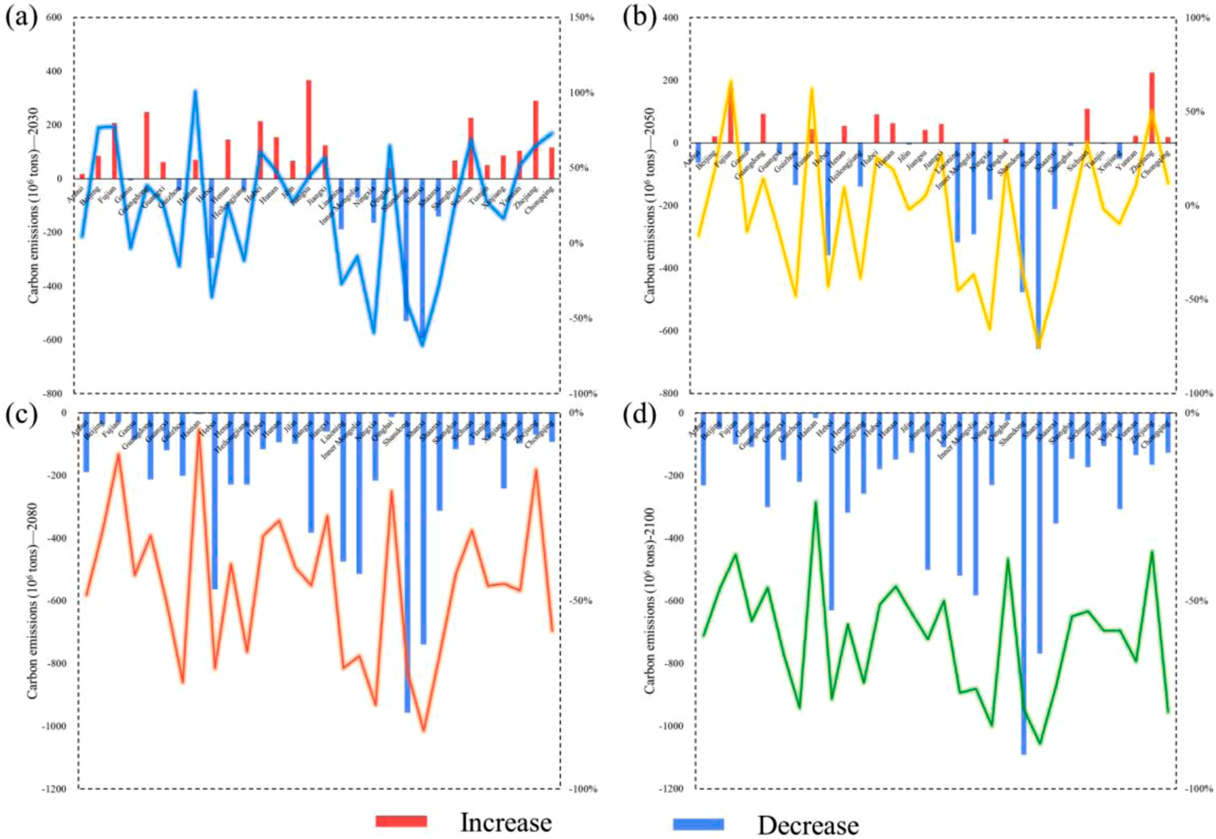

Fig. A.3.. Changes in carbon emissions compared with 2017 in the SSP4 scenario.

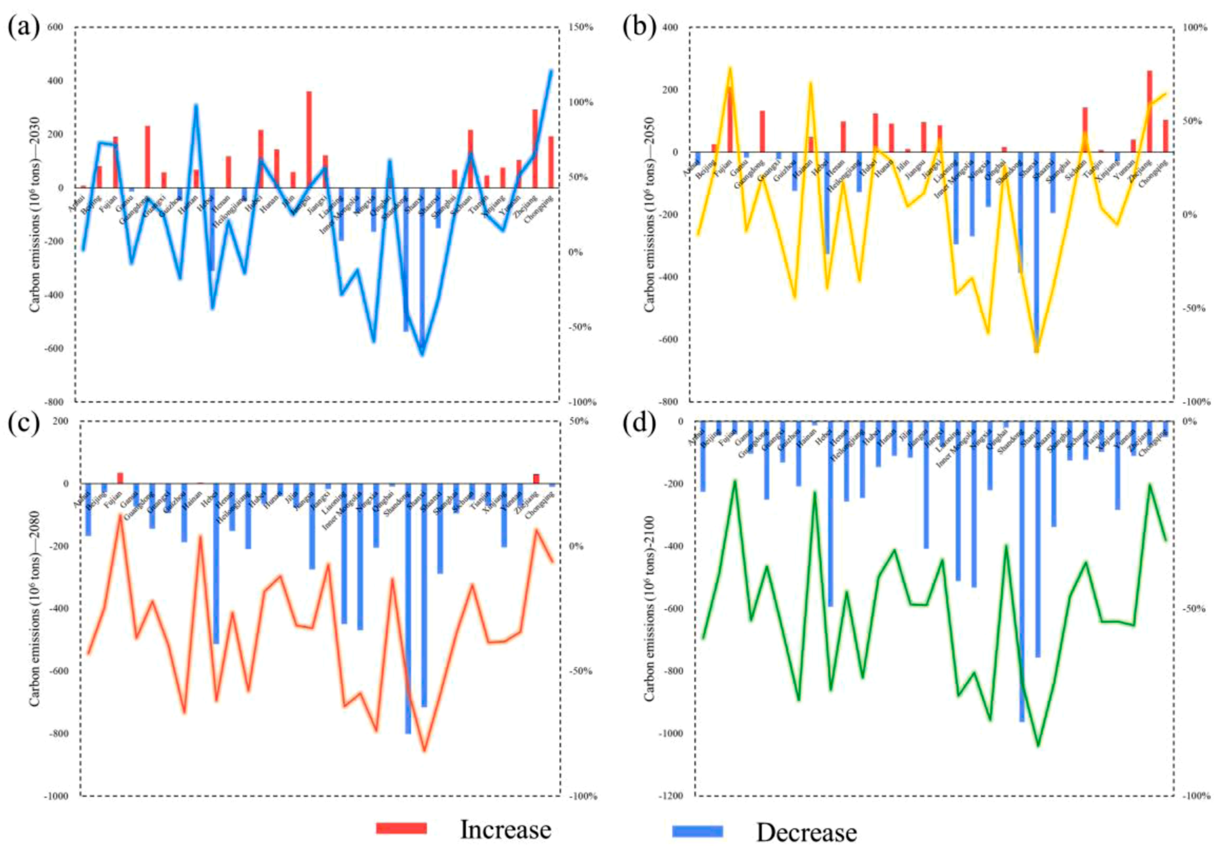

Fig. A.4.. Changes in carbon emissions compared with 2017 in the SSP5 scenario.

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