



Spatial spillover effects of urbanization on carbon emissions in the Yangtze River Delta urban agglomeration, China

Tiangui Lv^{1,2} · Han Hu¹ · Xinmin Zhang² · Hualin Xie² · Li Wang¹ · Shufei Fu¹

Received: 24 June 2021 / Accepted: 26 November 2021 / Published online: 15 January 2022
© The Author(s), under exclusive licence to Springer-Verlag GmbH Germany, part of Springer Nature 2021

Abstract

To achieve a win–win situation for both urbanization and carbon emissions reduction from a spatiotemporal perspective, we need to identify the salient links between urbanization and carbon emissions in different dimensions. Using 2008–2018 panel data on the Yangtze River Delta urban agglomeration, this paper constructs a Stochastic Impacts by Regression on Population, Affluence, and Technology (STIRPAT) model based on four dimensions of urbanization: population, economy, land, and ecology. Additionally, it uses a whole group of variables for reference, constructs a Spatial Durbin model (SDM) to estimate the spatial effect, and empirically investigates the spatial dependence of carbon emissions and the influence of various driving factors. The results show that (1) in the temporal dimension, the historical carbon emissions of the study area continue to increase. However, the extent to which they are doing so is slowing, the number of low carbon emissions areas has significantly decreased, the number of medium carbon emissions areas have significantly increased, the number of high and relatively high carbon emissions areas are relatively stable, and energy intensity continues to decline. (2) In the spatial dimension, Shanghai, Suzhou, and their surrounding cities have always been carbon emissions hotspots, high and relatively high carbon emissions areas are mainly concentrated in these cities. Low carbon emissions areas and cold spots are mainly distributed in Anhui Province. Medium carbon emissions areas show a great spatial and temporal evolution and are distributed in all provinces. (3) In the four dimensions of urbanization, per capita GDP will not only affect regional carbon emissions but also have a spatial spillover effect. For every 1% increase in the economic factors, carbon emissions in neighboring regions will increase by 0.38–0.43%. Population, economic, and technological factors have significant positive effects on carbon emissions, and economic factor is the most important factor. (4) In different dimensions of urbanization, there are obvious heterogeneities in the impacts of different factors on carbon emissions. Among them, the elasticity coefficient of per capita GDP and energy intensity is the smallest among the dimension of land urbanization, and the elasticity coefficient of the total population is the smallest among the dimension of population urbanization. Therefore, when formulating carbon emissions reduction policies, it is necessary to fully consider the spatial spillover effects, determine the optimal population size threshold, advocate for a low-carbon lifestyle, promote clean technology, and realize information exchange and policy interaction across regions from the perspective of holistic governance.

Keywords Multidimensional urbanization · Carbon emissions · STIRPAT model · Spatial Durbin model · Yangtze River Delta urban agglomeration

Responsible Editor: Eyup Dogan.

✉ Xinmin Zhang
zhangxm1217@yahoo.com

¹ School of Tourism and Urban Management, Jiangxi University of Finance and Economics, Nanchang 330013, China

² Institute of Ecological Civilization, Jiangxi University of Finance and Economics, Nanchang 330013, China

Introduction

Popular opinion recognizes carbon emissions as a key factor affecting the construction of an ecological civilization in China. The growth in carbon emissions is also a direct factor leading to global warming, greenhouse effects, and extreme weather events. Cities are China's largest carbon source. Population agglomeration, industrial transformation, and land changes resulting from urbanization have also had a profound impact on carbon emissions (Martínez-Zarzoso

and Maruotti 2011). At the same time, with the advancement of urbanization, the demand among people for a beautiful environment is increasing. By implementing a series of effective carbon emissions reduction policies, China's ecological environment has been improved to a certain extent. However, the contradiction between urban development and ecological protection due to rapid urbanization still cannot be ignored (Song 2021). Achieving the goals of reaching peak of carbon emissions by 2030 and reaching carbon neutrality by 2060 represents a practical problem. Exploring the mechanism through which urbanization impacts carbon emissions hold great value for overcoming the environmental constraints on urbanization development and enhancing regional sustainable development.

Many scholars have performed exploratory research investigating urbanization and carbon emissions, and the streams of literature can be categorized as follows. The first stream of literature focuses on the factors influencing carbon emissions in urbanization from both the macro and micro perspectives. Zhang et al. (2019) divided China into three regions based on different levels of urbanization to assess the impacts of various factors on China's carbon emissions at the national and regional levels. Adams et al. (2020) discussed the impact of factors such as electricity consumption on carbon emissions at various stages of urbanization in Sub-Saharan Africa (SSA). Their study found that the predicted impact of urbanization and transportation energy consumption on carbon emissions varies greatly among SSA countries. The second stream of literature focuses on the relationship between urbanization and carbon emissions. There are three main perspectives. According to the first, urbanization can help reduce carbon emissions through scale effects or environmental governance (Wang et al. 2020; Sharma 2011; Yilmaz et al. 2021). According to the second, urbanization exacerbates carbon emissions through the agglomeration of factors such as population and the economy or through the transformation of land use (Yang et al. 2018; Chen et al. 2019). According to the third, there is no obvious relevance between urbanization and carbon emissions (Sadorsky 2014). The scholars who hold the first two views generally believe that carbon emissions have a restrictive effect on urbanization. The third stream of literature focuses on the impact of multidimensional urbanization on carbon emissions. Scholars such as Liddle (2010) and Ahmad (2018) introduced land urbanization and other concepts based on an extension of urbanization into environmental research, and many scholars have begun to explore the mechanism driving the correlation between urbanization and carbon emissions based on multidimensional urbanization. Chen et al. (2020) found that population, land, and economic urbanization had significant positive effects on carbon emissions. At present, scholars recognize that urbanization is not unidimensional concept, and different scholars have decomposed

urbanization in different ways (Yang et al. 2020; Zhou et al. 2019). He et al. (2017) decomposed urbanization into four dimensions: population, economy, society, and space. Du et al. (2019) decomposed the urbanization system into the following three subsystems: the economy, population, and land. Considering that urbanization is a current trend that will continue into the future, this paper empirically studies the issues above from the perspective of the impact of multidimensional urbanization on carbon emissions.

In summary, many valuable research results have been obtained in research on the mechanism of urbanization and carbon emissions. However, although the existing literature has focused on the driving effect of multidimensional urbanization on carbon emissions, few studies have included the dimension of ecological urbanization as a category of analysis in a comparative analysis to explore the impact of multidimensional urbanization on carbon emissions. In addition, more in-depth research that investigates the spatial spillover effects of urbanization on carbon emissions by combining the indicators of various dimensions is needed.

Therefore, this paper uses 2008–2018 data of the Yangtze River Delta urban agglomeration and constructs a STIRPAT model based on the following four dimensions urbanization: population, economy, land, and ecology. Additionally, it uses the idea of a whole group of variables for reference, constructs a spatial panel model while considering the spatial effect to conduct comparative analysis, and discusses the uncertainty of the relationship between urbanization and carbon emissions.

Study area

The Yangtze River Delta urban agglomeration (Fig. 1) includes 27 cities in the Yangtze River Delta, with Shanghai, Nanjing, Hangzhou, Hefei, and Ningbo being the central cities. Its total area is 225,000 km², and it accounts for 2% of China's territory and 20% of China's GDP (Yu et al. 2020). Its rapid economic development has been accompanied by urbanization and regional integration of the Yangtze River Delta. In 2019, the State Council approved the overall plan for the Yangtze River Delta ecological and green integrated development demonstration zone, which started the construction of the beautiful China pioneer demonstration zone. The study area contains the most high-quality capital, human resources, science, technology and other resource elements in China. At the same time, however, due to its increasing energy demand, the problem of carbon emissions continues to be prominent. Therefore, identifying the path for future urbanization and carbon emissions in the study area holds great practical significance for achieving the carbon

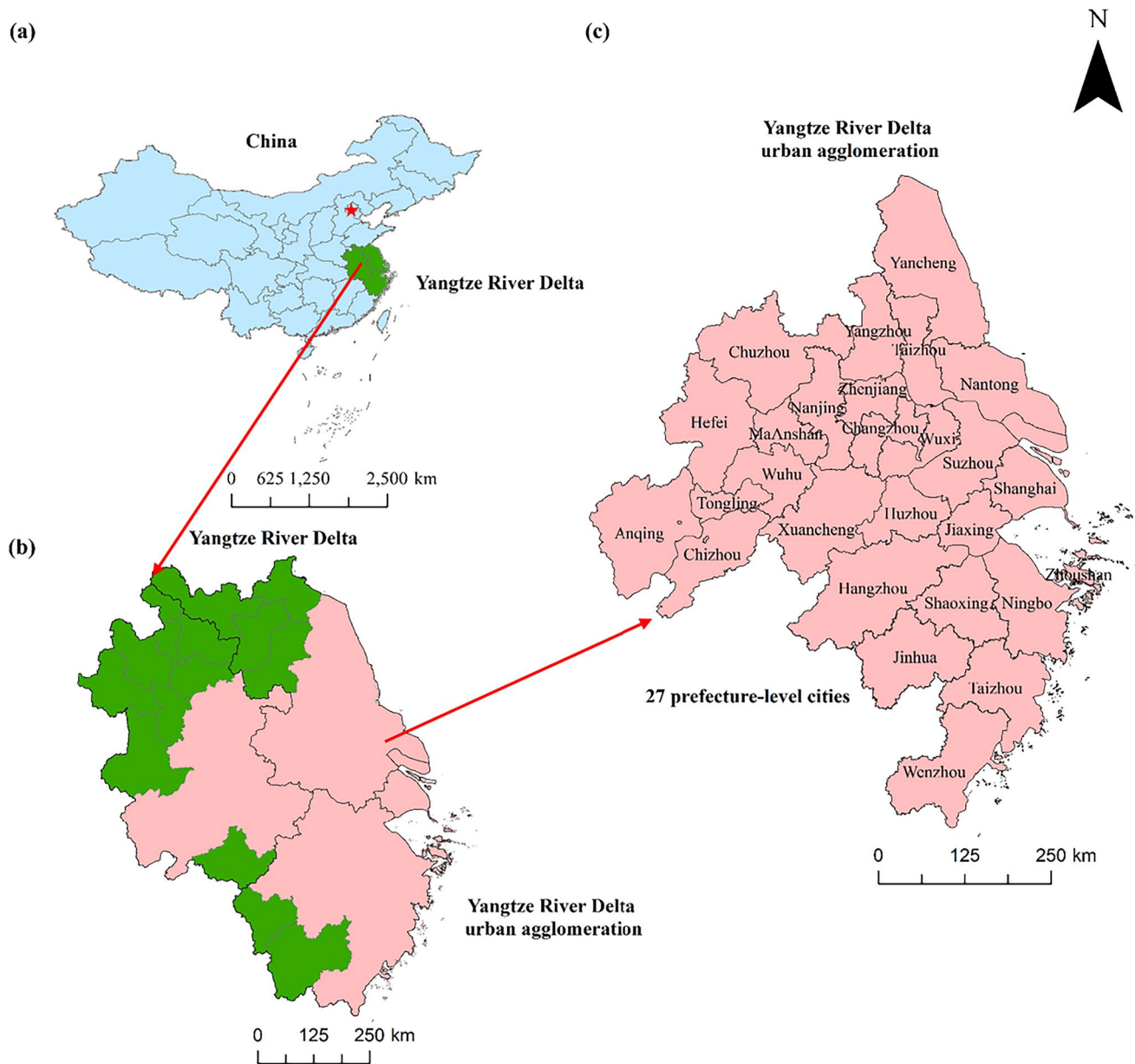


Fig. 1 Location of Yangtze River Delta urban agglomeration in China. (a) China, (b) Yangtze River Delta, and (c) 27 prefecture-level cities in Yangtze River Delta urban agglomeration

emissions reduction goals of both the urban agglomeration and the beautiful China pioneer demonstration zone.

Methodology and data sources

STIRPAT model

In studies investigating the relationship among economic growth, resources, and the environment, the IPAT framework proposed by Erlich and Holdren (1971) has been

widely used. This model is expressed as $I = P * A * T$, where I represents the environmental impact, P represents the population factor, A represents the economic factor, and T represents the technological factor. However, the IPAT model is too concise, and its assumption of unified unit elasticity conflicts with the hypothesis of the Environmental Kuznets Curve. To compensate for this weakness of the IPAT model, Dietz and Rosa (1997) built the STIRPAT model to make it possible to identify the driving factor with the most important environmental impact in empirical analyses. The basic equation is as follows:

$$I_{it} = \alpha P_{it}^\beta A_{it}^\gamma T_{it}^\delta e_{it} \tag{1}$$

In Eq. (1), i represents the country (region), t represents the year, $\alpha, \beta, \gamma,$ and δ represent the coefficients of $P, A,$ and $T,$ respectively, and e_{it} is the random error.

In addition, the STIRPAT model can be combined with the SDM to explore spatial correlation, heterogeneity, and spillover. The logarithmic form of the STIRPAT model can help eliminate some endogeneity problems. Referring to this practice, this paper constructs the model as follows:

$$\ln I_{it} = a + b \ln P_{it} + c \ln A_{it} + d \ln T_{it} + e \ln U_{it} + \varepsilon_{it} \tag{2}$$

In Eq. (2), i and t represent the prefecture-level city and year, respectively; $b, c, d,$ and e are the coefficients of the above variables; a is the constant term; and ε is the regression residual term. I represents the carbon emissions of a city; P represents the total population of a city; A represents the wealth level of a city, which is measured by the per capita GDP of the city; T represents the technological level of a city, which is characterized by the energy intensity of the city; and U represents the urbanization level of a city, which is further decomposed into four subsystems: population urbanization, economic urbanization, land urbanization and ecological urbanization (Li et al. 2019).

Exploratory spatial data analysis

Spatial autocorrelation statistics

Spatial autocorrelation refers to the potential correlation of variables in different spatial positions. Spatial autocorrelation is a measure of spatial dependence, and it includes global and local indicators. The global spatial autocorrelation indexes mainly include the global Moran’s I statistic and Geary’s C statistic, while the local spatial autocorrelation indexes generally include the local Moran’s index and the G_i index. This paper mainly uses Moran’s I index to test whether spatial autocorrelation exists, and we can establish a spatial econometric model on the basis of the result. The equation is as follows:

$$I = \frac{n \sum_{i=1}^n \sum_{j=1}^n W_{ij} (x_i - \bar{x})(x_j - \bar{x})}{(\sum_{i=1}^n \sum_{j=1}^n W_{ij}) \sum_{i=1}^n (x_i - \bar{x})^2} \tag{3}$$

In Eq. (3), x_i represents the carbon emissions of city $i,$ n represents the number of regions, and W represents the spatial weight matrix (Liu et al. 2018).

Spatial Weight Matrix

Before performing spatial econometric analysis, a spatial weight matrix is generally used to describe the adjacency

relationship between geographic units. The spatial weight matrix W generally uses a binary symmetric matrix to express the proximity between n spatial elements. W can be expressed as follows:

$$W = \begin{bmatrix} w_{11} & w_{12} & \cdots & w_{1n} \\ w_{21} & w_{22} & \cdots & w_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ w_{n1} & w_{n2} & \cdots & w_{nn} \end{bmatrix} \tag{4}$$

In Eq. (4), w_{ij} denotes the proximity between regions i and $j,$ and $w_{ij} = w_{ji}.$ Such a relationship can be measured based on the adjacency standard or distance standard, and the elements on the diagonal line are set to 0.

The weight matrix of adjacent space represents the relationship among geographical locations. In this paper, the weight matrix of adjacent space is defined by first-order R-adjacency, which is mainly used to measure the impact of carbon emissions between adjacent cities. It is expressed as follows in Eq. (5):

$$W_{ij} = \begin{cases} 1, & \text{city } i \text{ and } j \text{ share a common border} \\ 0, & \text{city } i \text{ and city } j \text{ share a common border or } i = j \end{cases} \tag{5}$$

Spatial Durbin model

Spatial econometric models have the advantages of both spatial effects and time effects. When the spatial lag of the explanatory variables affects the dependent variables, we should consider establishing an SDM. The SDM includes many widely used models, including the spatial lag of not only the dependent variables but also the independent variables. The equation is as follows:

$$y = \rho W_y + \beta X + \theta WX + \varepsilon \tag{6}$$

In Eq. (6), y is the explained variable; X is the explanatory variable, W is the spatial weight matrix; ρ is the spatial autoregressive coefficient; β and θ are the regression coefficients; and ε is the residual term (Liu and Xiao 2014).

Variable selection and data description

Results obtained using variable accounting methods and data sources

This paper selects carbon emissions as the result variable. Currently, there are no specialized carbon emissions data in China; thus, many studies calculated carbon emissions through energy consumption. In this paper, combined with the characteristics found in the energy statistical data of the study area, the total amount of fossil fuel energy consumed

is used as the calculation basis, and the calculation formula is as follows:

$$CE = \sum (E_i * \eta_i) \quad (7)$$

In Eq. (7), CE represents carbon emissions, E_i represents the consumption of energy i , and η_i is the carbon emissions coefficient of energy i . The conversion coefficient and carbon emissions coefficient of standard coal are shown in Table 1. This paper obtained data on the energy consumption of cities from 2008 to 2018, including the consumption of raw coal, coke, gasoline, kerosene, diesel, fuel oil, heat, electricity, and natural gas, from statistical yearbooks. Then, standard coal was converted based on the reference coefficient of energy converted into standard coal, and the carbon emissions were calculated by summing the carbon emissions coefficient provided by Zhao et al. (2016).

Control variables and data sources

Considering the theory of ecological economics and previous research results from studies on carbon emissions and urbanization, this paper selected the following core explanatory variables.

1. Population urbanization: The process of urbanization is accompanied by the transition of the population from low-carbon agricultural activities to high-carbon non-agricultural activities. Therefore, the proportion of the urban population, the urban population density, and the proportion of nonagricultural employees were compressed into a whole group of variables by using the concept described by Wang et al. (2017).
2. Land urbanization: Land is an important carrier of population and the economy. The process of urbanization has witnessed the transformation of land-use patterns, and it boosts carbon emissions. Therefore, three indicators

were selected to compress: the per unit area fiscal revenue, the proportion of the urban built-up area, and the per capita urban road area (Chen et al. 2020).

3. Economic urbanization: The economy is the driving force of urbanization, and it leads to changes in industry, trade, and residents' living standards, as well as an increase in carbon emissions (Ahmad and Zhao 2018). Therefore, for economic urbanization, per capita fiscal revenue, the proportion of fiscal revenue in GDP, and the level of regional trade openness were compressed.
4. Ecological urbanization: Urbanization has developed into a new era, and people's requirements for the environment have continued to increase. The expansion of ecological spaces with emission reduction effects has become a new trend in urbanization. Therefore, based on Shi (2020), the per capita park green area and the green coverage rate of the urban built-up area were selected.

In addition, the total population, per capita GDP, and energy intensity were introduced as control variables. All economic data were processed based on 2008 constant prices, and the regions involved in the administrative division change in Anhui Province were processed based on the current economic proportion to ensure that the data were current and consistent. The data were all derived from statistical yearbooks. The main variables in this paper are shown in Table 2.

Spatial and temporal evolution of carbon emissions in the Yangtze River Delta urban agglomeration

Analysis of temporal characteristics

The total carbon emissions and energy intensity of 27 prefecture-level cities in the study area were calculated. As shown in Fig. 2, ① based on the change in carbon emissions from 2008 to 2018, the carbon emissions of the study area increased from approximately 4000 million tons to 5000 million tons, showing an increasing trend, but the growth rate gradually slowed. ② Based on the change in energy intensity from 2008 to 2018, the energy intensity of the study area decreased from 0.8 to 0.4, showing a continuous decline. Notably, two rounds of sharp declines occurred in the 2009–2014 and 2017–2018 periods. The historical value shows that the carbon emissions of the study area are still increasing, but the continuous decline in energy intensity has shown a trend of carbon emissions reduction, allowing for optimism. This finding is mainly the result of the Yangtze River Delta's active promotion of industrial structure optimization in recent years and the establishment of a diversified clean energy supply system.

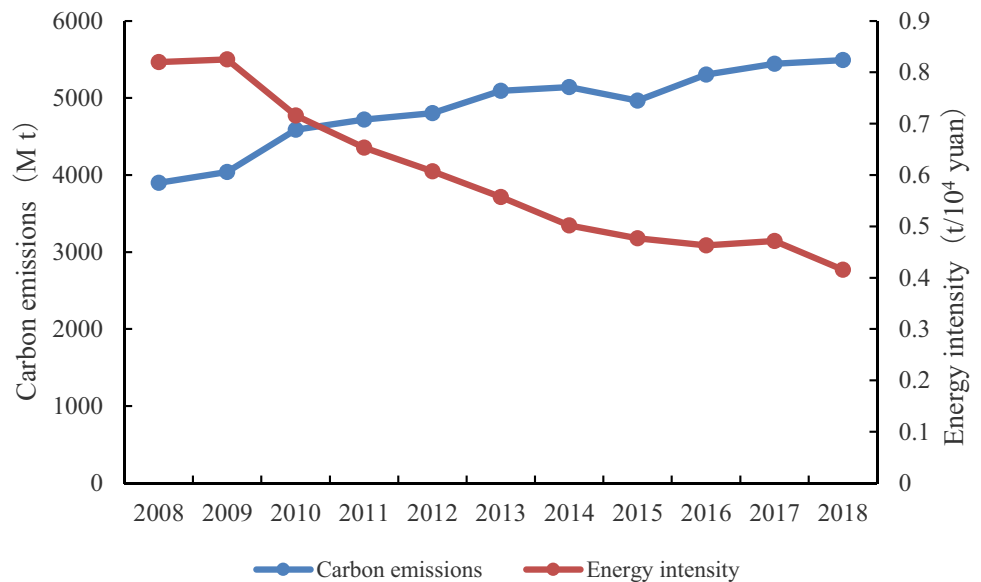
Table 1 Conversion coefficients and carbon emissions coefficients of standard coal

Energy types	Reference coefficient of standard coal	Carbon emissions coefficient
Raw coal	0.7143	0.7559
Coke	0.9714	0.8550
Gasoline	1.4714	0.5538
Kerosene	1.4714	0.5714
Diesel	1.4571	0.5921
Fuel oil	1.4286	0.6185
Heat	0.0341	0.2600
Electricity	1.2290	2.5255
Natural gas	1.3300	0.4483

Table 2 Indicators of each dimension

Variable types	Dimensions	Indexes	Units
Control variables	P	Population size	10 ⁴ persons
	A	Per capita GDP	yuan
	T	Energy intensity	tons of standard coal/10 ⁴ yuan
Independent variables	Population urbanization	Proportion of the urban population	%
		Urban population density	persons/km ²
		Proportion of nonagricultural employees	%
	Land urbanization	Per unit area fiscal revenue	10 ⁸ yuan/km ²
		Proportion of urban built-up area	%
		Per capita urban road area	m ²
	Economic urbanization	Per capita fiscal revenue	10 ⁸ yuan/10 ⁴ persons
		Proportion of fiscal revenue in GDP	%
		Regional trade openness	%
	Ecological urbanization	Per capita park green area	m ²
		Green coverage rate of urban built-up area	%

Fig. 2 Changes in carbon emissions and energy intensity of the Yangtze River Delta urban agglomeration spanning from 2008 to 2018



Analysis of spatial characteristics

The average carbon emissions of the study area in 2008, 2012, 2015, and 2018 were calculated. Referring to the division standard described by Huang et al. (2019), which is 0.5, 1, and 1.5 times the average carbon emissions in the selected years, the carbon emissions of the 27 prefecture-level cities were classified into the following four categories: a low carbon emissions area, medium carbon emissions area, relatively high carbon emissions area and high carbon emissions area. Figure 3 illustrates that the distribution of carbon emissions in the study area was not balanced and showed heterogeneity in the temporal and spatial dimensions. In general, from 2008 to 2018, the number of low carbon emissions areas decreased from 10

in 2008 to 5 in 2018, the number of medium carbon emissions areas increased from 9 in 2008 to 14 in 2018, and the number of relatively high carbon emissions areas and high carbon emissions areas were relatively stable, with values of 4 and 5, respectively. The low carbon emissions areas were mainly distributed in Anhui Province and scattered in Jiangsu and Zhejiang Provinces. By 2015, there were no low carbon emissions areas in Jiangsu Province. The distribution of medium carbon emissions areas greatly changed, as they gradually spread from central Jiangsu and eastern Zhejiang to northern Zhejiang and central Anhui. The high carbon emissions areas were mainly in the central cities of the study area, including Shanghai, Suzhou, Nanjing, Wuxi, and Ningbo. The relatively high carbon emissions areas were most scattered around the

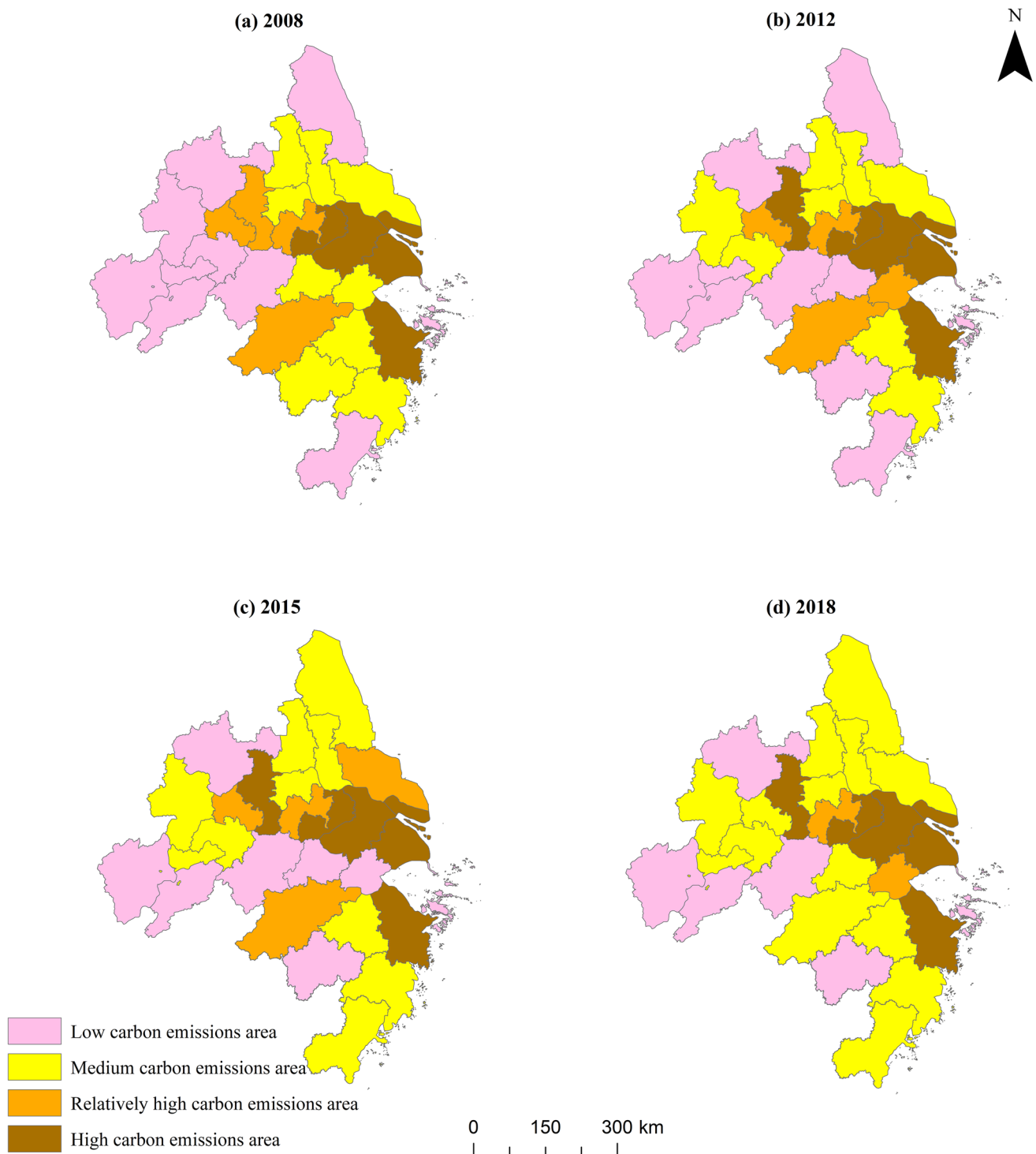


Fig. 3 Evolution of the spatial and temporal pattern of carbon emissions

high carbon emissions areas, including Changzhou, Hangzhou, MaAnshan, and other cities.

From the provincial perspective, Shanghai has always been a high carbon emissions area because it has developed nonagricultural industries, a dense population, a high

level of production, and high living energy consumption. Jiangsu Province was dominated by medium carbon emissions areas, relatively high carbon emissions areas, and high carbon emissions areas. Only Yancheng was a low carbon emissions area. The medium carbon emissions areas were

mainly concentrated in the three cities in central Jiangsu and Zhejiang, the relatively high carbon emissions areas were mainly in Changzhou, and the high carbon emissions areas were mainly Wuxi, Nanjing, and Suzhou. Yancheng is rich in wetlands and other ecological resources, and the carbon sink effects are strong. The industries in central Jiangsu are relatively developed. Although energy-saving industries have achieved better energy conservation in recent years, the pressure for energy conservation is still heavy. There are many industrial areas in cities in southern Jiangsu, such as Suzhou and Wuxi. Most of the top 100 industrial counties in China are located here, and the carbon source effects are strong. Zhejiang Province was dominated by medium carbon emissions areas, especially in the three cities located in northern Zhejiang. Jinhua was the main low carbon emissions area; Shaoxing, Taizhou, and Wenzhou were the main medium carbon emissions areas; Hangzhou was a relatively high carbon emissions area, and Ningbo was a high carbon emissions area. Jinhua has a large forest coverage rate and a significant effect as a green carbon sink. Shaoxing and other cities are important industrial cities in Zhejiang Province that consume more energy. Hangzhou and Ningbo are not only the industrial core cities of Zhejiang Province but also major population clusters facing both ecological risks and carbon emissions pressures. Anhui Province was dominated by low and medium carbon emissions areas. Only MaAnshan had a relatively high carbon emissions area, and there were no high carbon emissions areas. Since 2012, Hefei, Wuhu, and Tongling have gradually changed to medium carbon emissions areas, and Chuzhou, Chizhou, Anqing, and Xuancheng have always been low carbon emissions areas. In recent years, resource-based cities and industrial cities such as Chizhou and Chuzhou in Anhui Province have been actively seeking transformation and promoting the low-carbon development of the province's economy. However, the transformation and upgrading of MaAnshan is relatively lagging, and carbon emissions reduction is still an arduous task.

This paper used a spatial correlation analysis to test the spatial dependence of the carbon emissions of the study area. Table 3 reports the test results for the Moran's *I* index. Moran's *I* index was positive in each year from 2008 to 2018 and was significant test at the 5% level, indicating that there was a positive spatial correlation in carbon emissions. Therefore, it was necessary to use the spatial econometric model to conduct follow-up research. From the perspective of the index trend, Moran's *I* index was relatively stable, indicating that the spatial correlation of carbon emissions in the study area changed only minimally.

Based on the analysis of the Getis-Ord G_i^* statistics (Fig. 4), the hotspot areas changed minimally from 2008 to 2018 and were relatively concentrated. Shanghai and its surrounding cities were consistently hotspots, and Tongling was a cold spot in 2008; however, it was not significant in

Table 3 Moran's *I* index test results from 2008 to 2018

Year	<i>I</i>	<i>Z</i>	<i>p</i>
2008	0.301450**	2.426487	0.015246
2009	0.284982**	2.310147	0.020880
2010	0.312494**	2.476283	0.013276
2011	0.301079**	2.404716	0.016185
2012	0.318883**	2.537083	0.011178
2013	0.315984**	2.521992	0.011669
2014	0.335084***	2.661712	0.007774
2015	0.266273**	2.169922	0.030013
2016	0.356559***	2.826392	0.004708
2017	0.349479***	2.769987	0.005606
2018	0.348623***	2.770947	0.005589

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

2018. From the provincial perspective, Shanghai has always been a hotspot. Suzhou, Wuxi, and Changzhou in Jiangsu Province and Huzhou and Jiaxing in Zhejiang Province have always been hotspots. Tongling in Anhui Province was a cold spot in 2008. This distribution is due to the developed nonagricultural industries in Shanghai and its surrounding areas, and the excessive concentration of factors such as population, which have become the main carbon sources.

Through a comprehensive comparison of the results obtained using various methods of spatiotemporal evolution analysis, we found that ① in the temporal dimension, the historical carbon emissions of the study area are increasing, but the amplitude is slowing. The number of low carbon emissions areas has significantly decreased, the number of medium carbon emissions areas has significantly increased, the number of relatively high carbon emissions areas and high carbon emissions areas has been relatively stable, and energy intensity continues to decline. ② In the spatial dimension, the historical carbon emissions of the study area have significant spatial dependence and heterogeneity. The low carbon emissions areas are mainly distributed in Anhui, the medium carbon emissions areas are gradually spreading from central and eastern Jiangsu to northern Zhejiang and central Anhui, the high carbon emissions areas are mainly in the regional central city, and the relatively high carbon emissions areas are distributed around the high carbon emissions areas. Shanghai, Suzhou, and their surrounding cities have always been carbon emissions hotspots, while the low carbon emissions areas are mainly distributed in Tongling in Anhui Province. ③ From the provincial perspective, Shanghai has always been a high carbon emissions area. In Jiangsu Province, medium carbon emissions areas, relatively high carbon emissions areas, and high carbon emissions areas are dominant. In Zhejiang Province, medium carbon emissions areas are dominant. Thus, the carbon emissions zoning situation greatly changes. In Anhui Province, low carbon

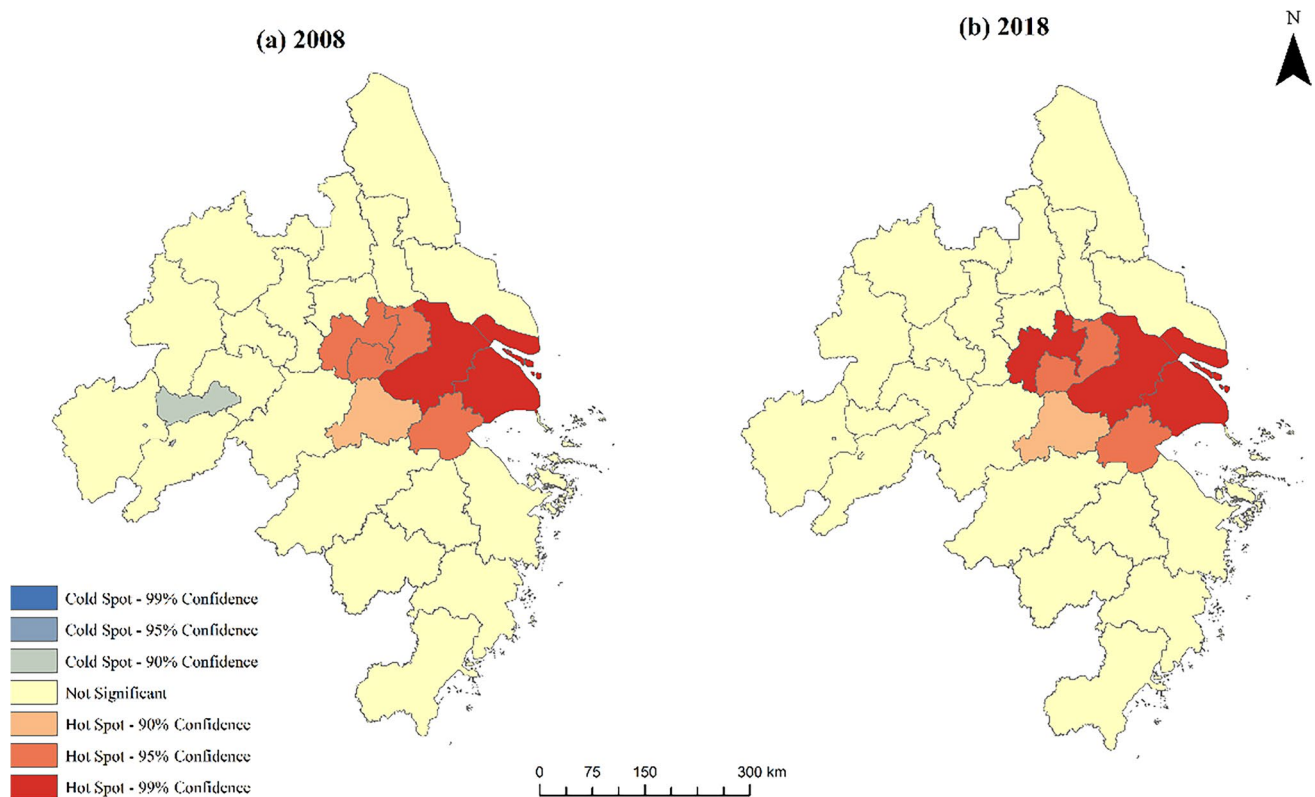


Fig. 4 Analysis of carbon emissions hotspots of the study area in 2008 and 2018

emissions areas and medium carbon emissions areas are dominant. Shanghai, Suzhou, Wuxi, and Changzhou in Jiangsu Province and Huzhou and Jiaxing in Zhejiang Province have always been hotspots. Tongling in Anhui Province was a cold spot in 2008.

Analysis of the factors influencing carbon emissions in the Yangtze River Delta urban agglomeration

Spatial panel model settings

The analysis above showed that there was a significant spatial correlation in carbon emissions in the study area. If this spatial correlation is ignored, the results could be biased, but the spatial econometric model can solve this problem. First, Lagrange multiplier (LM) and robust Lagrange multiplier (R-LM) tests were used to verify the need to use a spatial panel model. Then, the likelihood ratio (LR) test and Wald test were used to determine whether the SDM could degenerate into the SLM (spatial lag model) or SEM (spatial error model). The results reported in Table 4 show that the LR test and Wald test were significant; thus, the SDM could be used for the analysis. Furthermore, based on the results of

Table 4 Model test results

Test		Statistics	<i>p</i> -value
LM test	Spatial error	555.043	0.0000
	Spatial lag	409.134	0.0000
R-LM test	Spatial error	184.593	0.0000
	Spatial lag	38.6840	0.0000
LR test	Spatial error	15.120	0.0345
	Spatial lag	13.630	0.0582
Wald test	Spatial error	13.880	0.0534
	Spatial lag	15.000	0.0360
Hausman test		19.020	0.0148

the Hausman test, a fixed effect model was selected for the estimation (Hong et al. 2020).

Spatial econometric estimation and analysis of the results

Selection and estimation of spatial econometric models

First, ordinary least squares (OLS) estimation was used to estimate the four-dimensional models that did not include spatial effects. The results are shown in Table 5.

Table 5 Comparison of estimation results of two panel models

Variables	Common panel model				Spatial Durbin model			
	Population urbanization	Land urbanization	Economic urbanization	Ecological urbanization	Population urbanization	Land urbanization	Economic urbanization	Ecological urbanization
lnU	−0.0364 (0.0722)	0.2319** (0.0913)	0.0586 (0.3373)	−0.0639* (0.0378)	−0.0893 (0.0694)	0.2048** (0.0850)	0.3193 (0.3328)	−0.0380 (0.0362)
lnP	0.3644*** (0.1070)	0.3887*** (0.0961)	0.3873*** (0.0973)	0.3726*** (0.0971)	0.2523** (0.1045)	0.3205*** (0.0922)	0.3159*** (0.0932)	0.3076*** (0.0932)
lnA	0.5879*** (0.0530)	0.4701*** (0.0693)	0.5864*** (0.0530)	0.5500*** (0.0567)	0.3678*** (0.0829)	0.2877*** (0.0899)	0.3638*** (0.0852)	0.3618*** (0.0838)
lnT	0.1835*** (0.0429)	0.1639*** (0.0428)	0.1864*** (0.0425)	0.1864*** (0.0421)	0.2137*** (0.0415)	0.2011*** (0.0412)	0.2176*** (0.0406)	0.2213*** (0.0406)
W·lnU					0.0496 (0.1270)	0.0397 (0.1369)	0.3329 (0.3071)	0.0035 (0.0601)
W·lnP					−0.0655 (0.2278)	−0.0891 (0.2232)	−0.0460 (0.2309)	−0.0798 (0.2259)
W·lnA					0.4538*** (0.1299)	0.3891*** (0.1507)	0.4423*** (0.1252)	0.4103*** (0.1319)
W·lnT					0.1219 (0.0856)	0.1010 (0.0828)	0.0932 (0.0826)	0.0973 (0.0824)
R ²	0.4483	0.4608	0.4478	0.4536	0.5130	0.6032	0.6068	0.6135

By comparing the goodness-of-fit between the ordinary panel model and the SDM, we found that the fitting effect of the model was significantly improved after considering the spatial correlation of carbon emissions between cities, and the spatial lag term of the explanatory variable and the explained variable were significant at the 1% level, proving the need to use the spatial panel model. Table 5 shows that land urbanization had a significant positive driving effect on carbon emissions, population urbanization and ecological urbanization had a negative impact on carbon emissions, and economic urbanization had a positive impact on carbon emissions. However, the relationship between these three dimensions and carbon emissions were not statistically significant. In addition, the level of land urbanization had an impact only on a city’s carbon emissions and did not affect the adjacent areas; thus, there was no spatial spillover effect.

The SDM contains spatial lag variables and explained variables; therefore, this model cannot directly reflect the influence of the explanatory variables on the explained variables, but it can still obtain directional information from the results. In the case of significance at the 1% level, lnP, lnA, and lnT all had a significant positive driving effect on a city’s carbon emissions. Only lnA had a significant positive impact on carbon emissions in adjacent areas, and the other variables had no statistically significant impact on carbon emissions in adjacent areas.

Direct effect, indirect effect, and total effect

The results show that the elasticity coefficient and direct effect value of each variable differed due to the feedback effect of the spatial lag term. Therefore, to measure the influence of the independent variables on dependent variables, it was necessary to further estimate the direct effect, indirect effect, feedback effect, and total effect of the model. The direct effect refers to the average value of the change in carbon emissions caused by changes in the factors influencing carbon emissions. The direct effect includes the feedback effect, one part of which is derived from the explained variable of the spatial lag, while the other part is derived from the explained variable of the spatial lag that affects the carbon emissions of adjacent cities, which, in turn, will affect the carbon emissions of the local region. The indirect effect refers to the influence of local carbon emissions factors on the carbon emissions of adjacent areas. The total effect is the sum of the direct effect and indirect effect (Li et al. 2020; Liu et al. 2019) (Table 6).

Compared with the elasticity coefficients of the explanatory variables in the ordinary panel model shown in Table 5, the values of the direct effects reported in Table 6 are larger or smaller, indicating that the elastic coefficients of the ordinary panel model are overestimated or underestimated, respectively, because the spatial effects are not included in the ordinary panel model.

Table 6 Estimation results of spatial Durbin model

Variables		Population urbanization	Land urbanization	Economic urbanization	Ecological urbanization
lnU	Direct effect	−0.0884	0.2061**	0.3203	−0.0375
		−0.0704	−0.0861	−0.3367	−0.0366
	Indirect effect	0.0296	0.0074	0.2544	−0.0047
	Total effect	−0.1433	−0.1598	−0.3627	−0.068
		−0.0588	0.2135	0.5747	−0.0421
		−0.1513	−0.1775	−0.4699	−0.0723
lnP	Direct effect	0.2434***	0.3117***	0.3067***	0.2982***
		−0.0928	−0.0783	−0.0793	−0.0792
	Indirect effect	−0.0755	−0.0997	−0.0552	−0.0810
	Total effect	−0.211	−0.2051	−0.2132	−0.2133
		0.1679	0.2120	0.2515	0.2172
		−0.2077	−0.2023	−0.2078	−0.2109
lnA	Direct effect	0.3690***	0.2888**	0.3645***	0.3644***
		−0.0909	−0.0904	−0.0886	−0.0923
	Indirect effect	0.4317***	0.3811**	0.4104***	0.3813***
	Total effect	−0.1250	−0.1506	−0.1136	−0.1254
		0.8007***	0.6699***	0.7749***	0.7456***
		−0.0903	−0.1314	−0.0848	−0.1041
lnT	Direct effect	0.2158***	0.2033***	0.2200***	0.2239***
		−0.045	−0.0434	−0.0436	−0.0437
	Indirect effect	0.1070	0.0875	0.0763	0.0828
	Total effect	−0.0804	−0.0764	−0.075	−0.0755
		0.3229***	0.2908***	0.2963***	0.3067***
		−0.0845	−0.0827	−0.0814	−0.0808

- (1) Dimension of population urbanization: ① From the perspective of the direct effect, for each 1% increase in the total population, per capita GDP, and energy intensity, the level of carbon emissions will increase by 0.2434%, 0.3690%, and 0.2158%, respectively. Among these factors, per capita GDP has the most important effect on a city's carbon emissions. ② From the perspective of the feedback effect, the feedback effect of the per capita GDP is −0.0012%, accounting for 0.33% of the direct effect. This result is reflected in the fact that under certain conditions, a change in per capita GDP in this region will affect its carbon emissions by affecting the carbon emissions of adjacent regions. ③ From the perspective of the indirect effect, only per capita GDP has a spillover effect. Each 1% increase in per capita GDP has a 0.4317% impact on carbon emissions in neighboring areas.
- (2) Dimension of land urbanization: ① From the perspective of the direct effect, for each 1% increase in the level of land urbanization, the total population, per capita GDP, and energy intensity, the level of carbon emissions will increase by 0.2061%, 0.3117%, 0.2888%, and 0.2033%, respectively. Among these factors, per capita GDP and the total population have the most important effects on carbon emissions in this region. ② From the perspective of the feedback effect, the feedback effect of per capita GDP is −0.0011%, accounting for 0.38% of the direct effect. ③ From the perspective of the indirect effect, only per capita GDP has a spillover effect. Each 1% increase in per capita GDP has a 0.3811% impact on carbon emissions in neighboring areas.
- (3) Dimension of economic urbanization: ① From the perspective of the direct effect, for each 1% increase in the level of the total population, per capita GDP, and energy intensity, the level of carbon emissions will increase by 0.2061%, 0.3645%, and 0.2200%, respectively. ② From the perspective of the feedback effect, the feedback effect of per capita GDP is −0.0007%, accounting for 0.19% of the direct effects. ③ From the perspective of the indirect effect, only the per capita GDP has a spillover effect. Each 1% increase in per capita GDP has a 0.4104% impact on carbon emissions in neighboring areas.
- (4) Dimension of ecological urbanization: ① From the perspective of the direct effect, for each 1% increase in the level of ecological urbanization, the total popula-

tion, per capita GDP, and energy intensity, the level of carbon emissions will increase by 0.2982%, 0.3644%, and 0.2239%, respectively. Urbanization shows a non-significant negative impact. ② From the perspective of the feedback effect, the feedback effect of per capita GDP is -0.0026% , accounting for 0.71% of the direct effect. Among these factors, the total population has largest feedback effect, indicating that the population flow has an impact on carbon emissions. ③ From the perspective of the indirect effect, only per capita GDP has a spillover effect. Each 1% increase in per capita GDP has a 0.3813% impact on carbon emissions in neighboring areas.

Through this comparison, we found the following: ① Among the four dimensions of urbanization, only the level of land urbanization had a significant driving effect on carbon emissions, and there was no indirect effect. This shows that the urbanization development model of “development by land” in the past had a profound impact on carbon emissions. ② Among the four dimensions, lnA had significant feedback and indirect effects (spatial spillover effects), and for every 1% increase in the economic factor, the carbon emissions of neighboring areas will increase by 0.3811–0.4317%, reflecting the important impact of regional economic ties on carbon emissions. This result also verifies that carbon emissions reduction cannot be achieved in isolation, and regional linkages need to be integrated through a holistic approach. ③ The elasticity coefficient of per capita GDP and energy intensity was the smallest among the four subdimensions of land urbanization, and the elasticity coefficient of the total population was the smallest among the four subdimensions of population urbanization.

Causes of the differences in the results of the spatial econometric analysis between urbanization and carbon emissions

Based on the estimation results of the SDM and the causal analysis, we found the following:

- (1) Among the variables, lnP, lnA, and lnT had a significant positive impact on carbon emissions in the local region, and only lnA had a significant positive impact on the carbon emissions in adjacent regions. This result may be due to the increasing demand for private and public infrastructure and energy due to the expansion of the population, which is consistent with most research conclusions. The increase in per capita GDP has caused an increase in carbon emissions in local region and its neighboring areas. One possible reason is that regional economic growth and its radiation effect have caused an increase in residents' income levels and thus stimulated

growth in consumption and the demand for energy, both of which play a driving role in carbon emissions. Furthermore, economic growth attracts greater population migration and spatial agglomeration. Cross-regional population flow and the formation of economies of scale promote further economic growth. Furthermore, these factors exacerbate carbon emissions. Regarding energy intensity, the lower the energy intensity is, the lower the carbon emissions; thus, improving in the technology level will reduce carbon emissions because these regions are actively carrying out industrial transformation, adopting cleaner production technology, continuously improving their energy efficiency, optimizing their energy structure, and gradually establishing a low-carbon energy consumption system.

- (2) In the dimension of land urbanization, the urbanization level is positively correlated with carbon emissions. It may be that land urbanization is the process of transferring land-use types to nonagricultural industries. Compared with agriculture, nonagricultural industries consume more energy. However, in the past era of land-based development, industrialization and urbanization were accompanied by an expansion of construction land. This expansion caused greater changes in the land management mode or carbon emissions driven by ecosystem carbon sinks and the anthropogenic carbon emissions carried by various land-use types.
- (3) In the dimension of ecological urbanization, urbanization and carbon emissions show a nonsignificant negative inhibitory effect. The reason is that the increase in greening and park areas provides more green carbon sinks for cities to absorb and fix carbon. However, ecological urbanization has not yet produced the expected emission reduction effects.
- (4) Through horizontal comparison, it can be found that the elasticity coefficient of per capita GDP and energy intensity is the smallest among the four subdimensions of land urbanization, and the elastic coefficient of the total population is the smallest among the four subdimensions of population urbanization. This result may be because land urbanization carries some economic information and population urbanization carries some population information, decreasing the elasticity coefficient of the variables related to carbon emissions.

Conclusions and suggestions

Conclusions

Using 2008–2018 data on the Yangtze River Delta urban agglomeration, this paper integrates the existing research indicators of green urbanization and environmental carrying

capacity into the dimension of ecological urbanization and constructs a STIRPAT model based on four dimensions of urbanization: population, economy, land, and ecology. Drawing upon the concept of using a whole set of variables, this paper constructs an SDM to estimate carbon dioxide emissions considering of spatial effect. The spatial dependence of emissions and the spillover effect of the driving factors are analyzed. The main conclusions are as follows:

- (1) In the temporal dimension, the historical carbon emissions of the study area are increasing. However, the extent to which they are doing so is slowing. The number of low carbon emissions areas has been significantly decreased, the number of medium carbon emissions areas has significantly increased, the number of relatively high and high carbon emissions areas has been mostly stable, and energy intensity continues to decline.
- (2) In the spatial dimension, the carbon emissions of the study area have significant spatial dependence and spatial heterogeneity. Shanghai, Suzhou, and their surrounding cities are consistently carbon emissions hotspots, and the high and relatively high carbon emissions areas are mainly concentrated in these cities. The low carbon emissions areas and cold spots are mainly distributed in Anhui Province. Medium carbon emissions areas show a large temporal and spatial evolution and are distributed in all provinces, gradually spreading from central Jiangsu and eastern Zhejiang to northern Zhejiang and central Anhui.
- (3) There is a significant positive spatial correlation of carbon emissions in the study area. If the spatial correlation is ignored, the results could be biased. In the four dimensions of urbanization, per capita GDP will not only have an impact on carbon emissions in local region but also have a spatial spillover effect. For every 1% increase in the economic factor, carbon emissions in neighboring regions will increase by 0.38–0.43%. However, the urbanization level, the total population, and energy intensity affect only the carbon emissions of the local region, and they show no spatial spillover effect. The total population, per capita GDP, and energy intensity have significant positive effects on carbon emissions, and per capita GDP is the most important factor. Based on the empirical study, population migration, spatial agglomeration and economic growth have driving effects on carbon emissions, while technological progress has a restraining effect.
- (4) In different urbanization dimensions, there are obvious heterogeneities in the impact of different factors on carbon emissions. The R^2 of ecological urbanization is significantly higher than that of the other three urbanization dimensions. The elasticity coefficient of

per capita GDP and energy intensity is the smallest among the four dimensions of land urbanization, and the elasticity coefficient of the total population is the smallest among the four subdimensions of population urbanization. There is a positive correlation between the urbanization level and carbon emissions in the dimension of land urbanization, but the results are not significant in the other dimensions. Notably, urbanization shows a statistically nonsignificant negative blocking effect on carbon emissions in the dimension of ecological urbanization. From the perspective of the feedback effect, only $\ln A$ has a significant positive driving effect on carbon emissions in adjacent areas, and there is a spatial spillover effect, reflecting that the impact of regional economic ties on carbon emissions cannot be ignored.

Suggestions

- (1) The spatial correlation, heterogeneity, and spillover effects of carbon emissions and some driving factors should be considered. Thus, when formulating carbon emissions reduction policies, a platform and policy framework for regional environmental collaborative governance and holistic governance should be built under the framework of regional integration in the Yangtze River Delta. Information exchange and policy interaction should be promoted among city governments in environmental governance work. Additionally, regional policy exchanges and regional cooperation on carbon emissions reduction issues should be strengthened. It is also critical to give full play to the “demonstration effect” of energy conservation and emissions reduction in pilot cities such as Nanjing and to prevent marginal cities such as MaAnshan from competing in a race to the bottom and becoming a pollution paradise.
- (2) The total population, per capita GDP and energy intensity have significant impacts on carbon emissions. Therefore, when formulating low-carbon and carbon emissions reduction policies, China should first guide the reasonable migration of the population from high-carbon areas with Shanghai as the core to small and medium-sized cities, grasp the appropriate population of large cities such as Suzhou and Hangzhou, and determine the optimal population size threshold. Second, China should consider changes in consumption modes, lifestyle, and production mode, improve the energy consumption structure of residents, and improve the efficiency of resource utilization. Third, China should give full play to the role of technological progress in reducing carbon emissions, advocate low-carbon living concepts, promote environmental protection technologies, foster path dependence on cleaner production

technologies, and promote energy conservation and a reduction in consumption in industrial cities such as Wuxi and MaAnshan.

- (3) Carbon emissions reduction involves many factors and subjects and should be treated from a holistic governance perspective. Holistic governance can overcome administrative barriers through coordination and integration mechanisms, promote the mutual enhancement of policy objectives and tools among regions, and realize the overall interests of the system. Regarding carbon emissions reduction, China should not only pay attention to the differences in low-carbon policy design concepts between the eastern and western regions of the Yangtze River Delta and between core cities and their surrounding cities, but also consider the overlap and conflict in policy tools between provinces and cities. Information sharing and policy interaction can be achieved by establishing a joint meeting system for carbon neutrality in the Yangtze River Delta and a carbon emissions amplification data platform.

Notably, this paper attempts to classify based on the connotation of urbanization and introduces the dimension of ecological urbanization to research the relationship between carbon emissions and urbanization. Although there are some innovations in this research, there is still much room for improvement. Future research can further improve the richness of the ecological urbanization index from the perspective of carbon sources and carbon sinks and integrate indicators, such as the forest carbon sequestration capacity, into the research design.

Author contribution Tiangui Lv and Han Hu analyzed the data and wrote the original manuscript. Han Hu and Li Wang performed the experiments. Tiangui Lv, Xinmin Zhang, and Hualin Xie gave the direction of research and reviewed the manuscript. Xinmin Zhang and Shufei Fu revised the manuscript.

Funding This study was supported by the National Natural Science Foundation of China (No. 71864016), the Postdoctoral Science Foundation of China (No. 2017M622098), the Jiangxi Postdoctoral Science Foundation (No.2017KY55), the Postdoctoral Daily Funding of Jiangxi Province (No. 2017RC036), the Science and Technology Project of Jiangxi Education Department (No. GJJ200509 & GJJ200542), the Humanities and Social Sciences Project of Jiangxi Education Department (No. JC20201), the Educational Science Planning of Jiangxi Province (No. 21YB042), Special Fund Project for Graduate Innovation in Jiangxi Province (No. YC2021–S384), and the 16th Student Scientific Research Project of Jiangxi University of Finance and Economics (No. 20210913204025738).

Data availability The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request.

Declarations

Ethics approval and consent to participate Not applicable.

Consent for publication Not applicable.

Competing interests The authors declare no competing interests.

References

- Adams S, Boateng E, Acheampong AO (2020) Transport energy consumption and environmental quality: Does urbanization matter? *Sci Total Environ* 744:140617. <https://doi.org/10.1016/j.scitotenv.2020.140617>
- Ahmad M, Zhao ZY (2018) Empirics on linkages among industrialization, urbanization, energy consumption, CO₂ emissions and economic growth: a heterogeneous panel study of China. *Environ Sci Pollut Res* 25:30617–30632. <https://doi.org/10.1007/s11356-018-3054-3>
- Chen J, Wang L, Li Y (2020) Research on the impact of multi-dimensional urbanization on China's carbon emissions under the background of COP21. *J Environ Manage* 273:111–123. <https://doi.org/10.1016/j.jenvman.2020.111123>
- Chen S, Jin H, Lu Y (2019) Impact of urbanization on CO₂ emissions and energy consumption structure: A panel data analysis for Chinese prefecture-level cities. *Struct Change Econ D* 49:107–119. <https://doi.org/10.1016/j.strueco.2018.08.009>
- Dietz T, Rosa EA (1997) Effects of population and affluence on CO₂ emissions. *P Natl A Sci USA* 94:175–179. <https://doi.org/10.1073/pnas.94.1.175>
- Du Y, Wan Q, Liu H, Liu H, Kasper K, Peng J (2019) How does urbanization influence PM_{2.5} concentrations? Perspective of spillover effect of multi-dimensional urbanization impact. *J Clean Prod* 220:974–983. <https://doi.org/10.1016/j.jclepro.2019.02.222>
- Ehrlich PR, Holdren JP (1971) Impact of population growth. *Science* 171:1212–1217
- He J, Wang S, Liu Y, Ma H, Liu Q (2017) Examining the relationship between urbanization and the eco-environment using a coupling analysis: Case study of Shanghai, China. *Ecol Indic* 77:185–193. <https://doi.org/10.1016/j.ecolind.2017.01.017>
- Hong J, Gu J, He R, Wang X, Shen Q (2020) Unfolding the spatial spillover effects of urbanization on interregional energy connectivity: evidence from province-level data. *Energy* 196:1–31. <https://doi.org/10.1016/j.energy.2020.116990>
- Huang H, Qiao X, Zhang J, Li Y, Zeng Y (2019) Spatial temporal differentiation and influencing factors of regional tourism carbon emissions under the background of green development: a case study of the Yangtze River economic belt. *Econ geogr* 39:214–224
- Li J, Li S (2020) Energy investment, economic growth and carbon emissions in China—Empirical analysis based on spatial Durbin model. *Energy Policy* 140:111425. <https://doi.org/10.1016/j.enpol.2020.111425>
- Li Z, Li Y, Shao S (2019) Analysis of Influencing Factors and Trend Forecast of Carbon Emission from Energy Consumption in China Based on Expanded STIRPAT Model. *Energies* 12:30–44. <https://doi.org/10.3390/en12163054>
- Liddle B, Lung S (2010) Age-structure, urbanization, and climate change in developed countries: revisiting STIRPAT for disaggregated population and consumption-related environmental impacts. *Popul Environ* 31:317–343. <https://doi.org/10.1007/s11111-010-0101-5>

- Liu F, Liu C (2019) Regional disparity, spatial spillover effects of urbanisation and carbon emissions in China. *J Clean Prod* 241:118226. <https://doi.org/10.1016/j.jclepro.2019.118226>
- Liu N, Liu C, Xia Y, Da B (2018) Examining the coordination between urbanization and eco-environment using coupling and spatial analyses: A case study in China. *Ecol Indic* 93:1163–1175. <https://doi.org/10.1016/j.ecolind.2018.06.013>
- Liu Y, Xiao H, Zikhali P, Lv Y (2014) Carbon Emissions in China: A Spatial Econometric Analysis at the Regional Level. *Sustainability* 6(9):6005–6023. <https://doi.org/10.3390/su6096005>
- Martínez-Zarzoso I, Maruotti A (2011) The Impact of Urbanization on CO2 Emissions: Evidence from Developing Countries. *Ecol Econ* 70:1344–1353. <https://doi.org/10.1016/j.ecolecon.2011.02.009>
- Shi L, Cai Z, Ding X, Di R, Xiao Q (2020) What Factors Affect the Level of Green Urbanization in the Yellow River Basin in the Context of New-Type Urbanization? *Sustainability* 12(6):2488–2503. <https://doi.org/10.3390/su12062488>
- Song Z (2021) Economic growth and carbon emissions: Estimation of a panel threshold model for the transition process in China. *J Clean Prod* 278:123773. <https://doi.org/10.1016/j.jclepro.2020.123773>
- Sadorsky P (2014) The effect of urbanization on CO2 emissions in emerging economies. *Energ Econ* 41:147–153. <https://doi.org/10.1016/j.eneco.2013.11.007>
- Sharma SS (2011) Determinants of carbon dioxide emissions: Empirical evidence from 69 countries. *Appl Energ* 88:376–382. <https://doi.org/10.1016/j.apenergy.2010.07.022>
- Wang F, Fan W, Liu J, Wang G, Chai W (2020) The effect of urbanization and spatial agglomeration on carbon emissions in urban agglomeration. *Environ Sci Pollut Res* 8:1–13. <https://doi.org/10.1007/s11356-020-08597-4>
- Wang F, Qin Y, Liu J, Wu C (2017) Research on the influencing factors of carbon emissions from the perspective of multi-dimensional Urbanization: a spatial Durbin panel model based on China's provincial data. *China's population, resources and environment* 27(9):151–161. <https://doi.org/10.12062/cpre.20170434> (In Chinese)
- Yang L, Xia H, Zhang X, Yuan S (2018) What matters for carbon emissions in regional sectors? A China study of extended STIRPAT model. *J Clean Prod* 180:595–602. <https://doi.org/10.1016/j.jclepro.2018.01.116>
- Yilmaz S, Sezen I, Sari EN (2021) The relationships between ecological urbanization, green areas, and air pollution in Erzurum/Turkey. *Environ Ecol Stat* 9:004846
- Yu X, Wu Z, Zheng H, Li M, Tan T (2020) How urban agglomeration improve the emission efficiency? A spatial econometric analysis of the Yangtze River Delta Urban Agglomeration in China. *J Environ Manage* 263:260–268. <https://doi.org/10.1016/j.jenvman.2019.110061>
- Yang Y, Li J, Zhu G, Guan X, Zhu W (2020) The impact of multi-dimensional urbanization on PM2.5 concentrations in 261 cities of China. *IEEE Access* 99:96199–96209. <https://doi.org/10.1109/access.2020.2995507>
- Zhang S, Zhao T (2019) Identifying major influencing factors of CO2 emissions in China: Regional disparities analysis based on STIRPAT model from 1996 to 2015. *Atmos Environ* 207:136–147. <https://doi.org/10.1016/j.atmosenv.2018.12.040>
- Zhao DL, Li T (2016) Variation characteristics and influencing factors of carbon emissions in the process of urbanization in China. *Journal of Peking University (Natural Science Edition)* 52:947–958. <https://doi.org/10.13209/j.0479-8023.2016.060> (In Chinese)
- Zhou C, Wang S, Wang J (2019) Examining the influences of urbanization on carbon dioxide emissions in the Yangtze River Delta, China: Kuznets curve relationship. *Sci Total Environ* 675:472–482. <https://doi.org/10.1016/j.scitotenv.2019.04.269>

Publisher's note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.