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

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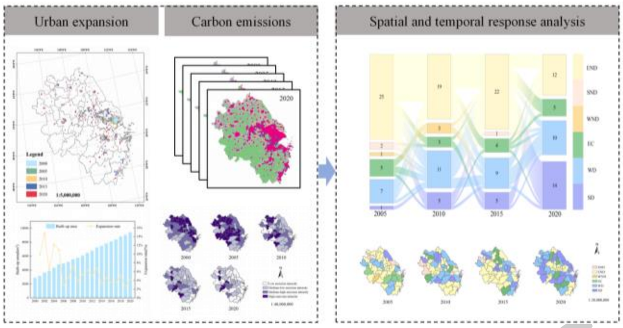
Graphical abstract



Abstract

Dynamically understanding the spatial and temporal evolution of the relationship between carbon emissions and the process of urbanization is of great significance for reducing greenhouse gas emissions and promoting the high-quality development of the regional economy. In this paper, the characteristics of the urban expansion in China's Yangtze River Delta Urban Agglomeration (YRDUA) from 2000 to 2020 are analyzed using nighttime light data, each city's carbon emission intensity is calculated by combining statistics on carbon emissions, and a quantitative study on the relationship between carbon emissions and urban expansion is conducted. The results of this study indicate that from 2000 to 2020, the built-up area in the YRDUA continued to expand. The expansion rate exhibited a fluctuating evolution pattern of increasing and decreasing and the carbon emission intensity decreased year after year. The urban expansion in the YRDUA promoted an increase in carbon emissions, but decoupling also occurred and transitioned from expansion of negative decoupling to weak decoupling and strong decoupling. By 2020, 70% of the cities in the YRDUA were in a state of decoupling. The research results will provide a scientific basis for future urban planning and the formulation of energy conservation and emission reduction policies.

Keywords: nighttime light data, urban built-up area extraction, standard deviation ellipse, decoupling analysis.

1. Introduction

An urban agglomeration is a new form of spatial organization with a mega-city as the core and three or more large cities as constituent units. The core area is closely linked to the surrounding areas through a highly developed transportation network, forming a spatially compact, economically connected and regionally integrated urban agglomeration (He *et al.* 2021). Although urban expansion has driven economic development, it has also triggered a series of environmental problems, including frequent occurrences of the heat island effect (Chen *et al.* 2022b; Mo *et al.* 2024; Huang *et al.* 2024), air pollution (Fan and Xu, 2020; Zhang *et al.* 2022; Zhou, 2024), and deterioration of the water environment (Itsukushima and Ohtsuki, 2021; Liang *et al.* 2020). Regarding the process of economic development of urban agglomerations, it is obvious that there is a high concentration of resources, a high degree of industrial agglomeration, rapid population growth, and frequent travel. However, the over exploitation of natural resources, inefficient use of energy, and high emissions from heavy industry all lead to increasingly severe carbon emissions.

China is a large country with a large population and a major global energy consumer and carbon emitter, and the issue of carbon emissions is of great concern (Feng *et al.* 2019; Yang and Bai, 2020; Jin and Lei, 2024). During the 75th session of the United Nations General Assembly in September 2020, China unveiled a dual-carbon goal for the first time, striving to peak carbon emissions by 2030 and achieve carbon neutrality by 2060 (Chen *et al.* 2022a; Hu *et al.* 2021; Zhang and Li, 2022). Determining the spatial and temporal differences in carbon emissions is a prerequisite for accelerating low-carbon development of urban agglomerations and realizing the dual-carbon goal.

Investigations into urban expansion have primarily concentrated on its spatiotemporal progression, driving mechanisms, predictive modeling, and the analysis of urban expansion patterns and ecological landscapes. Scholars have used multi-source remote sensing data to study changes in urban spatial patterns globally (Xu *et al.* 2020; Zhang *et al.* 2020) as well as specific analyses at the country and city scales, particularly in developing countries experiencing rapid urbanization (Zhen *et al.* 2018; Monkkonen *et al.* 2018; Matsa *et al.* 2021; Rustiadi *et al.* 2021; Mohammadi *et al.* 2022; Gambo *et al.* 2021; Ismael, 2020). Dutta estimated the expansion of impervious surfaces in New Delhi on the basis of a vegetation-impervious surface-soil model, and reported that as the population density continuously increased, the urban area would expand to the surrounding areas (Dutta *et al.* 2021). Mandal examined the urban development trends, including the direction and magnitude of expansion in Kolkata and its surrounding regions (Mandal *et al.* 2019). Xu investigated urban growth in Africa and the transformations in morphological attributes, utilizing urban land use density as a basis (Xu *et al.* 2019). Other scholars have analyzed the process of urban expansion and its driving force (Yin *et al.* 2022), and their findings have shown that the main causes of urban expansion are taxation policies, economic activity, and population growth (Fan and Zhou, 2019; Cai *et al.* 2020; Rijal *et al.* 2020; Guo and Zhang, 2021). Additionally, their research indicated that it is spatially heterogeneous and the characters of urban expansion significantly differs across various city sizes (Fei and Zhao, 2019; Li and Li, 2019; Wu *et al.* 2021).

In urban carbon emissions research, scholars have mainly focused on the total amount, intensity, efficiency, performance, and other aspects of carbon emissions. For example, Wang used stochastic frontier modeling to understand China's carbon emission efficiency from 2000 to 2010, and found that the average carbon emission efficiency increased by nearly 4.1% during this period (Wang and Jiang, 2017). Zhou used a three-stage data envelopment analysis (DEA) model to evaluate the carbon dioxide emissions of China's construction industry, and the results showed that the carbon dioxide emission efficiency of China's construction industry is generally low. Among all regions, the eastern region has the highest carbon emission efficiency, followed by the central and western regions (Zhou and Yu, 2021). The drivers of carbon emissions have attracted extensive attention from scholars (Qin *et al.* 2021; Liu and Song, 2020; Li *et al.* 2020; Murshed *et al.* 2022; Zhou *et al.* 2023). Some scholars have proposed the use of the carbon emission Kuznets curve based on the environmental Kuznets curve (EKC), and have tested it using various methods, but no consistent conclusions have been reached (Sarkodie *et al.* 2020; Pan and Zhang, 2020; Ji and Xue, 2022).

Research on urban expansion and carbon emissions has yielded rich results, but few studies have analyzed the spatial and temporal evolution of the relationship between urban expansion and carbon emissions. In view of this, this paper investigated the relationship between the spatial and temporal responses of urban expansion and carbon emissions in the YRDUA from 2000 to 2020. In this paper, we extracted the built-up areas of China's Yangtze River Delta Urban Agglomeration (YRDUA) from 2000 to 2020 based on the nighttime light data and analyzed the urban expansion characteristics in time and space. The existing carbon emission data for urban energy consumption and nighttime light data were used to construct a fitting model to retrieve the missing carbon emission data. This enabled the analysis of the spatial and temporal differences in carbon emissions in the YRDUA and the computation of the decoupling index, which elucidates the dynamic relationship between urban growth and carbon emissions over time. The research results provide scientific references for decision-makers in the YRDUA to formulate energy-saving and emission-reduction policies and low-carbon city development strategies.

2. Study area overview and data

2.1. Study area

The YRDUA is located on the eastern coast of China, includes the entirety of Shanghai, Jiangsu, Zhejiang, and Anhui provinces, contains 41 prefecture-level cities, and has a total area of approximately 358,000 km^2 (**Figure 1**). In 2022, the gross domestic product (GDP) of the YRDUA was 29.03 trillion yuan, accounting for approximately 24% of China's total GDP that year, making it one of the key growth poles driving China's economic development. Since 2000, the YRDUA has experienced rapid economic development and population growth, significant changes in land use, and continuous expansion of the size of built-up areas in cities. However, its huge economic output and rapid urban expansion have generated many negative effects on the environment. Due to the burning of large quantities of fossil fuels, which led to a year-on-year increase in regional carbon emissions, especially from 2016 to 2020, the annual average growth rate of carbon emissions in the YRDUA reached 2.4% (Liu *et al.* 2022). Determining how to optimize the structure of urban expansion while guaranteeing scientific development, and exploring the spatial and temporal relationship between carbon emissions and urban expansion have become the key to achieving sustainable development.

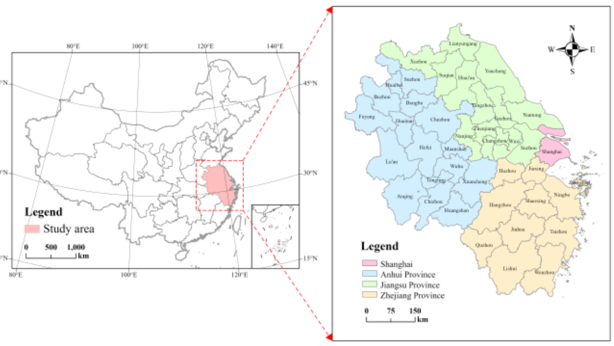


Figure 1. Map of the geographic location of the YRDUA

2.2. Data sources

The raw nighttime light data used in this study were obtained from the National Oceanographic and Atmospheric Administration/National Geophysical Data Center (NOAA/NGDC) website(https://ngdc.noaa.gov), and two nighttime light datasets, the Defense Meteorological Satellite Program/Operational Linescan System

(DMSP/OLS) dataset for 2000–2013 and the National Polar-orbiting Partnership/Visible Infrared Imaging Radiometer Suite (NPP/VIIRS) dataset for 2012–2020, were selected (Zhang *et al.* 2023). Due to the incompatibility of the two datasets in terms of the spatial resolution, sensor sensitivity, and spectral response mode, it was necessary to processing the nighttime light data. The DMSP/OLS data were processed with saturation correction, sensor correction, and time-series correction, the NPP/VIIRS data were processed with noise reduction, etc., and the two datasets were consistency-corrected and fitted to obtain long-term series of nighttime light data of 2000-2020. The data for the built-up area in the study area were obtained from the China Urban Statistical Yearbook, and the related economic data were derived from provincial and municipal statistical yearbooks. The data on carbon emissions of each city were derived from China Emission Accounts and Datasets (CEADs).

3. Research methodology

3.1. Urban expansion

To better demonstrate the urban spatial expansion results, in this study, the expansion speed and the expansion intensity difference index were selected to characterize the urban expansion.

3.1.1. Expansion speed

The expansion speed refers to the yearly average growth area of the urban built-up areas within a certain time range, and is one of the most common indicators to study urban expansion. The formula is as follows:

$$K_T = \frac{U_b - U_a}{T} \tag{1}$$

where K_T is the expansion speed in a region during a certain research period; U_a and U_b are built-up areas in the region at the beginning and end of period under study, respectively; and T denotes the duration of the study period.

3.1.2. Expansion intensity difference index

The expansion intensity difference index is the ratio between the growth rate of the urban expansion in a certain region and that of the whole research region. It can be used to reflected the difference in the urban expansion intensity during different periods. The formula is as follows:

$$\mathrm{UEDI}_n = \frac{\left|U_n^{t_2} - U_n^{t_1}\right| \times U^{t_1}}{\left|U^{t_2} - U^{t_1}\right| \times U_n^{t_1}} \tag{2}$$

where UEDI_n is the expansion intensity difference index of urban built-up area of the n^th^ region in a certain period; $U_n^{t_1}$ and $U_n^{t_2}$ are the built-up areas of the n^th^ region at t_1 and t_2, respectively; and U^{t_1} and U^{t_2} are the built-up areas of the total YRDUA at t_1 and t_2, respectively.

3.2. Carbon emissions

Based on the nighttime light data, carbon emissions were retrieved, and on this basis, the carbon emission intensity of each city was calculated and standard deviation ellipse analysis was performed to characterize the carbon emissions.

3.2.1. Carbon emission retrieval model

Based on nighttime light images of the study area from 2000 to 2020, the total nighttime light value of each city was obtained using the zoning statistics method and Equation (3), and it was fitted with the carbon emission data. The corresponding formula is as follows:

$$\mathrm{TDN} = \sum_{i=1}^{n} DN_i \tag{3}$$

where TDN is the total nighttime light value in a given city, DN_i is the nighttime light value of the i^{th} pixel, and n is the count of pixels.

3.2.2. Carbon emission intensity

The carbon emission intensity is defined as carbon dioxide emission per unit of GDP, which is an important indicator for characterizing the economic development quality and the relationship between economy and environment. It can be used to measure the city's level of low-carbon development. To ensure the rigor of the study and to make the research indicators comparable, the carbon emission intensity was selected to characterize the carbon emissions. The formula for calculating the carbon emission intensity is as follows:

$$CI_{it} = CE_{it} / GDP_{it} \tag{4}$$

where CI is carbon emission intensity, CE is carbon dioxide emissions, GDP is the gross domestic product per unit, t is the year, and i is the region.

3.2.3. Standard deviation ellipse

The standard deviation ellipse method has a good effect regarding the spatial distribution and directional analysis of the data, which is introduced in this paper to study the spatial and temporal evolution of carbon emissions in the YRDUA during the period 2000-2020. The center of gravity is calculated by the following formula:

$$\overline{X} = \frac{\sum_{i=1}^{n} w_i x_i}{\sum_{i=1}^{n} w_i} \tag{5}$$

$$\overline{Y} = \frac{\sum_{i=1}^{n} w_i y_i}{\sum_{i=1}^{n} w_i} \tag{6}$$

where $\overline{X}$ and $\overline{Y}$ denote the position of the gravity center on the x- and y-axes, respectively; x_i and y_i denote the position of the i^{th} region on the x- and y-axes, respectively; w_i denotes the carbon emissions in the i^{th} region.

3.3. Relationship between urban expansion and carbon emissions

3.3.1. Synergy expansion index

The synergy expansion index is a quantitative analysis method applied to analyze the coordination or equilibrium relationship between different elements inside a thing. The study utilizes the synergy expansion index to calculate the quantitative effect between carbon emissions and urban expansion. The calculation formula is as follows:

$$Q=\sqrt{(\alpha A+\beta C)\left\{\frac{AC}{\left[(A+C)/2\right]^{2}}\right\}^{m}} \tag{7}$$

where Q is the synergistic expansion index; A is the annual average expansion rate of the city; C is the annual average carbon emission rate of the city; and m is the moderating coefficient (m is usually taken as a real number greater than 2, and 3 is taken here). α and β are the weights to be determined, and urban expansion and carbon emission are considered to be of equal importance, thus $\alpha=\beta=0.5$

3.3.2. Decoupling analysis

Decoupling refers to a blockage of the link between economic growth and resource consumption or environmental pollution (Fan *et al.* 2023). If both are in a state of growth, but the pace of economic growth is greater than the pace of resource consumption or environmental pollution, it is relative decoupling. If economic growth is accompanied by a reduction in resource consumption or environmental pollution, it is absolute decoupling. Relative decoupling occurs first and eventually becomes absolute decoupling under human control.

In this study, we used the decoupling state analysis model proposed by Tapio to analyze European transportation carbon emissions and economic growth (Tapio, 2005), and we calculated the decoupling index of urban expansion and the carbon emissions in each city. The calculation formula is as follows:

$$D=\frac{(C_{i,t+n}-C_{i,t})/C_{i,t}}{(A_{i,t+n}-A_{i,t})/A_{i,t}} \tag{8}$$

where D is the decoupling index; $A_{i,t+n}$ and $A_{i,t}$ are the area of the built-up area in the i^th^ region in year (t + n) and the area of the built-up area in year t, respectively; and $C_{i,t+n}$ and $C_{i,t}$ are the total carbon emissions in year (t + n) and year t of the i^th^ region, respectively.

Based on the relationship reflected in the decoupling index, the states of decoupling can be divided into eight types (**Table 1**).

Table 1. States of decoupling by Tapio

States	Degrees	Environment pressure	Driving factors	Decoupling
Negative decoupling (ND)	Strong negative decoupling(SND)	>0	<0	<0
	Expansive negative decoupling(END)	>0	>0	>1.2
	Weak negative decoupling(WND)	<0	<0	0-0.8
Decoupling(D)	Strong decoupling (SD)	<0	>0	<0
	Weak decoupling (WD)	>0	>0	0-0.8
	Recessive decoupling (RD)	<0	<0	>1.2
Coupling(C)	Expansive coupling (EC)	>0	>0	0.8-1.2
	Recessive coupling (RC)	<0	<0	0.8-1.2

4. Results and analysis

4.1. Characterization of urban expansion

4.1.1. Urban built-up area extraction

By means of the reference comparison method, the spatial extent of the built-up area in 2000, 2005, 2010, 2015 and 2020 were extracted (**Figure 2**). As can be seen from the figure, the built-up area in the YRDUA expanded significantly in the period 2000-2020. The cities along the Yangtze River were linearly distributed and developed along the east-west orientation. In particular, the southern part of the Yangtze River, Shanghai, Suzhou, Wuxi, Changzhou and Nanjing developed rapidly. In addition, Hangzhou and Hefei, as provincial capitals, had relatively high levels of land urbanization.

4.1.2. Analysis of spatial and temporal differences in urban expansion

Figure 3 shows the built-up area and growth rate in the YRDUA from 2000 to 2020. As can be seen from **Figure 3**, the built-up area in the YRDUA continuously grew during the past 20 years, from 2,875 km^2 in 2000 to 9,409 km^2 in 2020, with a total growth of 6,534 km^2 and a growth rate of 227%. From 2000 to 2020, the expansion rate of the YRDUA exhibited a fluctuating evolution pattern of increasing and decreasing. The significant change in the expansion rate from 2001 to 2005 may have been related to China's entry into the World Trade Organization in 2001, and the active exploration of urban development mode in the YRDUA. After 2015, the expansion rate decreased significantly and entered a period of stable expansion.

According to the magnitude of the urban expansion speed, we categorized urban expansion into four types: high expansion (expansion speed of greater than 10 km^2/a), fast expansion (6–10 km^2/a), medium expansion (2–6 km^2/a), and low expansion (< 2 km^2/a) (**Figure 4**).

As shown in **Figure 4**, there were obvious differences in the urban expansion speed among the cities in the YRDUA, and the overall center of gravity of the high expansion shifted toward the northwest during the study period. From 2000 to 2005, the urban expansion speed in Shanghai, Suzhou, Wuxi, Nanjing, Hangzhou, Jiaxing, Ningbo, Hefei and Fuyang was greater than 10 km^2/a, i.e., high expansion. From 2005 to 2010, the expansion speed of Nantong and Xuzhou increased significantly, from low expansion, medium expansion to high expansion; those of Lianyungang and Suqian increased from medium expansion to fast expansion; and those of Chizhou and Xuancheng increased from low expansion to medium expansion. From 2010 to 2015, the expansion speeds of most cities increased, and the cities with high expansion were mostly concentrated in the east and predominantly in Jiangsu Province. During this period, with the acceleration of the economic construction in the Yangtze River Delta region, the development trend of surrounding cities with Shanghai as the center was gradually formed. In particular, the cities adjacent to Shanghai, attracted a large number of foreign population and development investment, and the vitality of the city was further stimulated. From 2015 to 2020, Anqing and Wuhu in Anhui Province and Huai'an in Jiangsu Province changed to high expansion. Some cities entered the mature stage of urban expansion, and their expansion speed slowed down.

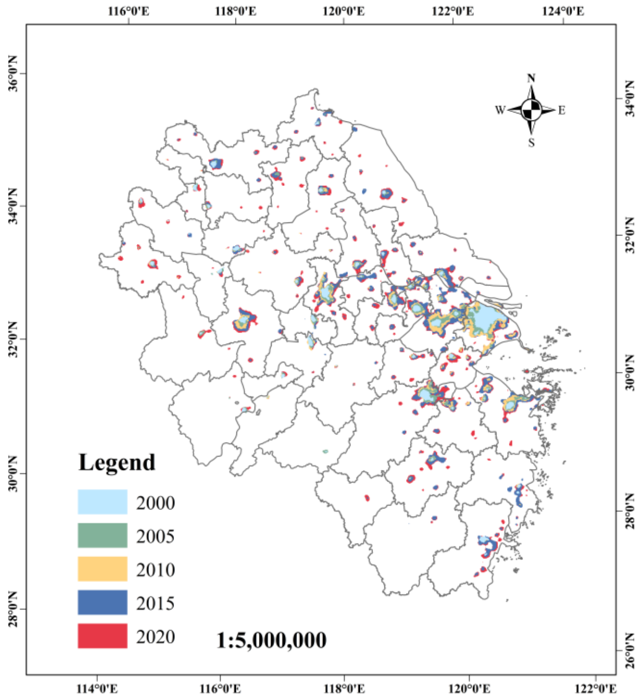


Figure 2. Expansion process of the built-up area in the YRDUA from 2000 to 2020

The expansion intensity difference index refers to the ratio of the growth rate of the urban expansion of a single city to that of the entire study area during the study period. The index makes the land expansion rate of different spatial units comparable, and is suitable for horizontal comparison of urban land expansion intensities among different spatial units.

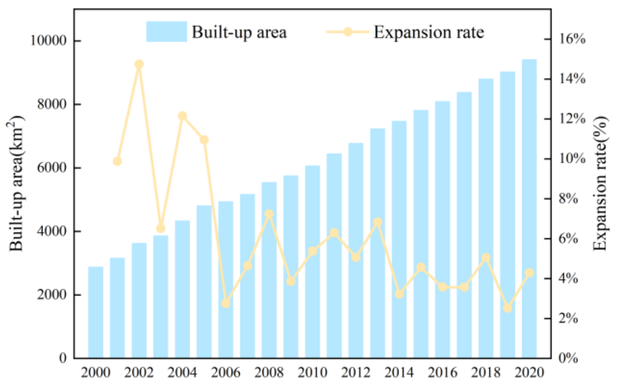


Figure 3. Built-up area and expansion rate of the YRDUA from 2000 to 2020

According to the magnitude of the expansion intensity difference index, urban expansion in the study area was categorized into five types: high-speed (>2), fast (1.2–2), medium-speed (0.8–1.2), low-speed (0.4–0.8), and slow (<0.4). **Table 2** lists the expansion intensity difference index of major cities.

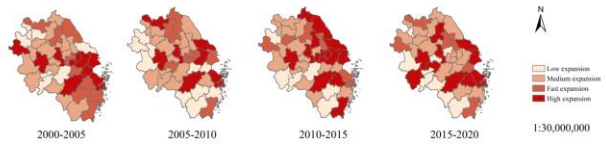


Figure 4. Spatial distribution of the expansion rate of the YRDUA from 2000 to 2020

The results show that from 2000 to 2005, the urban built-up areas in Nanjing, Jiaxing, Shaoxing, and Fuyang underwent high-speed expansion. From 2005 to 2010, the cities underwent high-speed expansion were Xuzhou, Suzhou, Nantong, Ningbo, Chuzhou, Fuyang. Between 2010 and 2015, the largest urban expansion intensity occurred in Shaoxing (3.34), and the smallest occurred in Xuzhou (0.23). Among the provincial capital cities, during the period 2015–2020, Shanghai underwent medium-speed expansion, Nanjing underwent low-speed expansion, Hangzhou underwent fast expansion, and Hefei underwent medium-speed expansion.

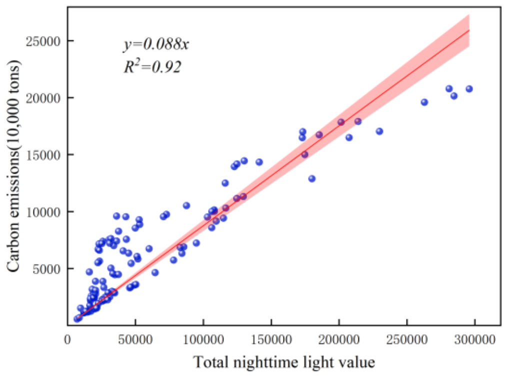


Figure 5. Fitting analysis of carbon emissions and total nighttime light value

4.2. Characterization of carbon emissions

4.2.1. Construction of carbon emission retrieval model

A linear regression equation was obtained based on the calculated total nighttime light value of each city and the statistical carbon emissions in the corresponding years (**Figure 5**).

The results show a significant linear correlation between the two, and the goodness of fit is 0.92. The results of the fit are as follows:

$$C_{it} = 0.088 \times DN_{it}$$

where C_{it} is the carbon emissions (10,000 tons) of city *i* in year *t*, and DN_{it} is the total value of the nighttime light in city *i* in year *t*.

Table 2. Expansion intensity difference index of major cities in the YRDUA

	2000-2005	2005-2010	2010-2015	2015-2020
Shanghai	0.73	0.21	0.51	1.17
Nanjing	2.30	0.77	0.74	0.73
Wuxi	1.32	0.73	1.43	0.31
Xuzhou	0.98	3.80	0.23	0.67
Changzhou	0.78	1.75	2.14	0.53
Suzhou	1.88	2.55	1.32	0.24
Nantong	0.07	4.42	2.16	2.00
Hangzhou	1.15	1.17	0.76	1.54
Ningbo	1.12	4.62	0.62	0.85
Wenzhou	0.45	0.89	1.22	0.78
Jiaxing	2.03	0.62	0.56	1.87
Shaoxing	2.31	0.81	3.34	1.35
Jinhua	1.44	0.28	0.38	1.83
Hefei	1.18	1.66	0.93	1.02
Wuhu	0.59	1.56	0.75	2.48
Bengbu	0.78	1.28	1.06	0.53
Maanshan	1.09	0.67	0.65	0.47
Tongling	0.13	1.24	1.97	0.32
Anqing	1.09	1.78	0.35	4.02
Chuzhou	1.13	2.30	1.35	1.16
Fuyang	4.66	2.05	2.04	1.24

Due to the limited carbon emission data for prefecture-level cities included in the statistical data, some areas were missing, and it was difficult to ensure the continuity of the year. Therefore, the fitting formula was used to study the carbon emissions in the YRDUA. Using the natural breakpoint method for hierarchical rendering, a simulated carbon emission distribution map was obtained. As shown in **Figure 6**, the total value of the nighttime light in each city in the YRDUA exhibited an increasing trend from 2000 to 2020, indicating that the carbon emissions of each city increased.

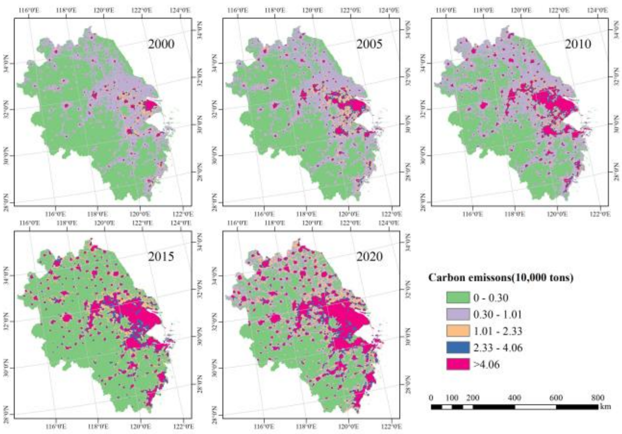


Figure 6. Carbon emissions in the YRDUA based on the total value of the nighttime light

4.2.2. Spatial and temporal differences in carbon emissions

To intuitively reflect the spatial evolution of the carbon emission intensities of each city within the YRDUA, five time cross-sections of data (2000, 2005, 2010, 2015, and 2020) were selected for analysis. In addition, according to the level of the carbon emission intensity, it was divided into four grades: low (0–0.8 t/billion yuan), medium-low (0.8–1.6 t/billion yuan), medium-high (1.6–2.4 t/billion yuan), and high (>2.4 t/billion yuan) (**Figure 7**).

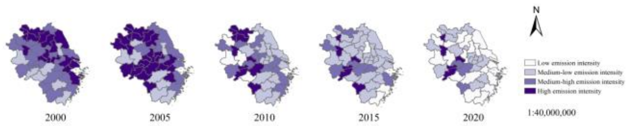


Figure 7. Spatial distribution of carbon emission intensity in the YRDUA from 2000 to 2020

In terms of the stages, in 2000, Shanghai had in a high emission intensity, and the carbon emission intensities of cities in Jiangsu Province were significantly higher than that of the cities in Zhejiang and Anhui. In 2005, the carbon emission intensities in some areas of the YRDUA increased compared with those in the previous stage. Most areas of Anhui Province increased from medium-low and medium-high emission intensities to high emission intensities. Shaoxing, Huzhou and Quzhou in Zhejiang Province increased from medium-low emission intensities to high emission intensities. Shanghai decreased from high emission intensity to medium-high emission intensity. Yangzhou and Yancheng in Jiangsu Province decreased from high emission intensities to medium-high emission intensities. In 2010, the carbon emission intensity of the YRDUA overall showed a significant drop from the previous stage. Shanghai changed to a medium-low emission intensity, and some cities in Anhui Province decreased from high and medium-high emission intensity to medium-low and low emission intensity. The decreasing trend in the carbon emission intensity for 2015 compared with the previous period was not significant. The main change was that the cities of Yangzhou, Wenzhou and Taizhou changed to low emission intensity. In 2020, Shanghai achieved a low carbon status; cities in Jiangsu Province and cities in Zhejiang Province, except for Quzhou, had low-medium and low emission intensity; and most of the cities in Anhui Province shifted to low-medium and low emission intensity.

To further study the spatial and temporal evolution features of the carbon emissions of the cities in the YRDUA, the standard deviation ellipse method was adopted to study the migration of the center of gravity of the carbon emissions. As can be seen from **Figure 8**, the centers of gravity of the standard deviation ellipse in the study area from 2000 to 2020 were all located in Jiangsu Province, and they migrated toward the southwest. Among them, the center of gravity was located in Yixing City in 2000. From 2000 to 2005, it migrated northwestward by 36.76 km to Danyang City. From 2005 to 2010, it migrated southeastward by 15.64 km to Jintan District. From 2010 to 2015, it migrated southwestward by 40.69 km to Liyang City. From 2015 to 2020, it migrated northwestward by 24.61 km to Lishui District. From the long axis of the standard deviation ellipse, the distribution of the carbon emissions in the YRDUA exhibited a certain directionality, which was roughly consistent with the north-south geographic direction of the study area, suggesting that the spatial distribution of the carbon emissions was closely related to each city's geographic orientation. From the perspective of the rotation angle, the rotation angle of the standard deviation ellipse changed by 1.99° from 2000 to 2020, suggesting that the center of gravity of the carbon emissions in the YRDUA did not change greatly during the past 20 years.

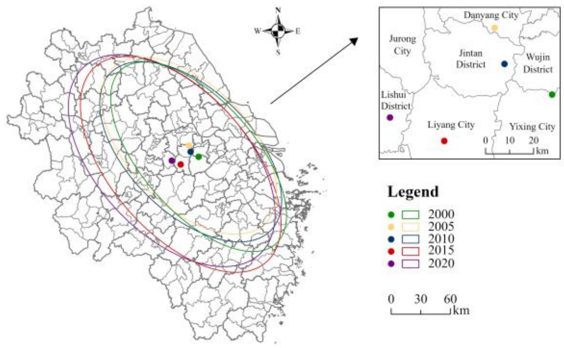


Figure 8. Change trend of the spatial distribution pattern of the carbon emissions and the migration trajectory of the center of gravity

4.3. Study of the effects of urban expansion on carbon emissions

In this study, we explored the spatial and temporal evolution of the relationship between urban expansion and carbon emissions by calculating the synergistic expansion index. **Table 4** presents the results of the synergistic expansion index.

Table 3. Standard deviation elliptic parameter

Year	Center X(°E)	Center Y(°N)	Long semi-axis(km)	Short semi-axis(km)	Angle of rotation(°)
2000	119.83	31.53	293.19	141.56	138.52
2005	119.63	31.82	273.94	152.34	135.60
2010	119.65	31.68	282.79	155.17	134.60
2015	119.32	31.43	326.94	175.22	138.86
2020	119.11	31.55	323.45	185.67	136.53

Table 4. Synergistic expansion index of urban expansion and carbon emissions in the YRDUA from 2000 to 2020

Time period	Annual average expansion rate(%)	Annual average carbon emission rate(%)	synergistic expansion index
2000-2005	13.51	20.50	0.39
2005-2010	5.40	10.31	0.24
2010-2015	5.92	4.86	0.23
2015-2020	4.10	1.05	0.07
2000-2020	11.62	15.07	0.36

In the first stage, from 2000 to 2005, the synergistic expansion index between the urban expansion and carbon emissions in the YRDUA was 0.39, indicating that the synergistic expansion relationship between the two was strong. Urban expansion and carbon emissions were in a state of simultaneous growth and coordinated expansion. Urban expansion promoted an increase in carbon emissions. During periods 2005–2010 and 2010–2015, the synergy expansion indices were 0.24 and 0.23, respectively, and the synergistic effect was lower than that in the first stage. From 2015 to 2020, the synergistic expansion index was only 0.07, indicating that the synergistic relationship between the urban expansion and carbon emissions was weak. The overall synergistic expansion index from 2000 to 2020 was 0.36, which was higher than the indices during the three sub-periods, indicating the importance of exploring the synergistic expansion process. Although the synergistic expansion index between the urban expansion and carbon emissions of the YRDUA in each sub-period from 2000 to 2020 was strong or weak, the overall synergistic expansion relationship between the two was significant.

The synergistic effect between the urban expansion and carbon emissions was obvious, but there were differences between regions. In this study, the decoupling index between the urban growth and carbon emissions in the YRDUA was computed using the Tapio decoupling model. Strong decoupling is the best decoupling state; that is, urban expansion is accompanied by a decrease in carbon emissions. Weak negative decoupling is the worst decoupling state; that is, urban expansion is negatively correlated with carbon emissions, and carbon emissions increase as the size of the city decreases. The rest of the states are between these two. **Figure 9** shows the change in the decoupling status of the YRDUA.

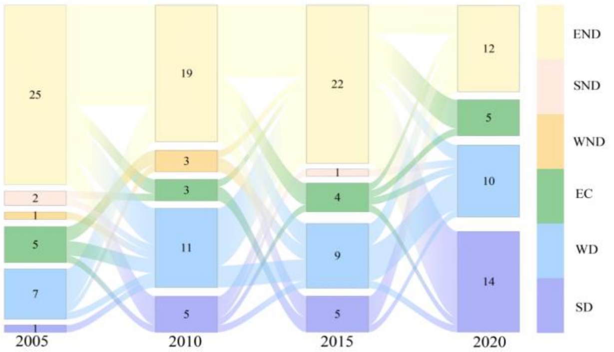


Figure 9. Changes in the decoupling status in the YRDUA

From 2000 to 2020, the decoupling state of the YRDUA shifted from expansion negative decoupling to strong decoupling and weak decoupling, and the decoupling level gradually increased, indicating that although the total carbon emissions increased with urban expansion, the growth rate decreased. In 2005, most of the cities in the YRDUA were in a negative decoupling state, of which 25 were in an expansion negative decoupling state, accounting for 60.98%. From 2005 to 2010, some of the cities shifted from negative decoupling to coupling and decoupling. Among them, five cities shifted from expansion negative decoupling to weak decoupling, and four cities changed to strong decoupling. From 2010 to 2015, carbon emissions increased significantly due to rapid urban expansion, and a small number of cities experienced a regression in their decoupling statuses, from strong decoupling and weak decoupling to expansion negative decoupling. From 2015 to 2020, the majority of the cities (12) shifted from expansion negative decoupling to strong decoupling. By 2020, 14 cities in the YRDUA were in a strong decoupling state, and 10 cities were in a weak decoupling state.

To deeply investigate the situation of the decoupling status in the YRDUA, the decoupling status of each city was spatially visualized (**Figure 10**). In 2005, Shanghai was in a state of weak decoupling, some of the cities in Zhejiang Province were in a state of initial decoupling, and most of the cities in Jiangsu and Anhui provinces were in a state of expansive negative decoupling, which may have been related to the fact that this was the early stage of urban expansion and to the adoption of a crude economic growth approach to increase the output value. From 2005 to 2010, Shanghai changed from weak decoupling to expansive negative decoupling, and the decoupling level of most cities in Jiangsu Province and Anhui Province increased, from expansive negative decoupling to expansive coupling and weak decoupling.. By 2020, urban development in the cities had reached a more mature stage, and China also paid increasing attention to carbon emissions. Most of the cities in the YRDUA were in a state of decoupling. Among them, Shanghai, Nantong, Yancheng, Huai'an, Hangzhou, Ningbo, Huzhou, Zhoushan, Anqing, Bengbu, Lu'an, Huainan, Huaibei, and Huangshan all had a strong decoupling status. This indicates that the cities had achieved a more desirable relationship between carbon emissions and urban expansion by emphasizing environmental protection while developing the economy.

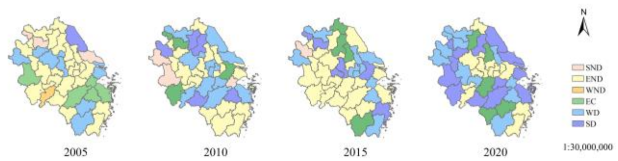


Figure 10. Decoupling index of the carbon emissions and urban expansion in the YRDUA

5. Discussion

5.1. Cause analysis

During the evolution of urban expansion from 2000 to 2020, there were significant differences in the expansion of cities in the YRDUA. The high-speed expansion areas were mainly located in Shanghai and some cities in Jiangsu and Zhejiang provinces. Except Hefei and Fuyang, most cities in Anhui Province underwent medium-speed, low-speed or slow expansion. In addition to the changes in expansion speed and intensity due to administrative division adjustments in individual years, urban expansion was mainly closely related to the economic level, industrial structure, population size, and other factors. Especially for some resource-based industrial cities, the urban expansion intensity difference index was higher in the early stage due to the large industrial output value. But as the status of conventional energy declines, whether we can seize the opportunity to adjust the industrial structure and achieve a new round of economic growth is crucial to the direction of urban expansion intensity. The carbon emission intensity of the YRDUA from 2000 to 2010 was relatively high with most of the cities in high and medium-high emission intensity. This may be due to the fact that in the early stage of its development, the YRDUA was oriented towards "economic growth", and while the economy grew, carbon emissions also continued to grow, and at a higher rate than the economic growth. From 2011 to 2020, the carbon emission intensity of each city decreased, which was closely related to the planning outline promulgated in 2011. The outline clearly sets targets for the reduction of carbon emission intensity, compulsorily restricts the carbon emissions of each city, promotes the establishment of a carbon emission trading market, greatly reduces the energy consumption intensity, and promotes low-carbon development. Encouraged by this policy, enterprises have actively engaged in green production practices, contributing to the gradual realization of the decoupled status of the cities (Lei *et al.* 2024a).

5.2. Suggestions on the development of the YRDUA

There is a significant correlation between urban expansion and carbon emissions, and the following suggestions are made to promote the sustainable development of the YRDUA.

(1) We should promote a low-carbon and recycling development model for the YRDUA and give full play to the

two-way interaction between the environment and high-quality economic development (Tian *et al.* 2024). We should adjust the industrial structure, develop low-carbon industries, support the development of regional strategic emerging industries, improve energy efficiency, and achieve green development. We should also promote the transformation of economic development achievements into social governance, increase the investment in environmental governance, improve governance of the environment, and form a virtuous circle of sustainable development.

(2) We should strengthen regional coordinated development; provide policy support; shift resources to cities with slower development in the northern, southern, and western parts of urban agglomerations; improve infrastructure construction such as transportation. In addition, we should strengthen economic and technological cooperation within an urban agglomeration, narrow the gap between economic growth and green development among cities, and promote low-carbon integrated development of the YRDUA.

(3) We should develop different low-carbon development strategies for urbanization that consider the specific development characteristics of each city and local conditions. For core cities, it is necessary to focus on a innovation drive on the basis of maintaining economic development, optimizing the energy structure, and developing an innovative green economy. For ordinary cities, it is necessary to carry out urban expansion in a reasonable manner, optimize the urban structure, regulate the implementation of environmental protection taxes (Lei *et al.* 2024b), accelerate the transformation of industrial structure and the construction of a green industrial structure system, and develop low-energy-consumption, low-pollution industries with urban characteristics to achieve synergistic development of urban expansion and carbon emission reduction.

5.3. Strengths and limitations of this study

This study explores the relationship between urban expansion and carbon emissions in the YRDUA from the perspective of synergistic development, which can provide scientific references for the formulation of low-carbon city development strategies and urban land use planning. The use of nighttime light data to retrieve carbon emissions makes up for the shortcomings of the limited carbon emission data of prefecture-level cities included in the statistical data, and the lack of annual continuity in some areas. However, this study only discusses the relationship between urban expansion and carbon emissions in a certain region (YRDUA) during a certain period of time (2000-2020), and important time points are selected from 2000, 2005, 2010, 2015, and 2020, without conducting research on more years. Due to the existence of spatial and temporal heterogeneity, the development level of different regions and different periods varies greatly, which makes the selection of a unified model for the calculation of carbon emissions and the actual situation has a certain error. At the same time, due to the significant differences in socio-economic development levels between different regions, there is a certain deviation in the explanation of the correlation between urban expansion and carbon emissions. In the future, the scope of the study should be increased, and different types of cities should be discussed from a more comprehensive perspective, so as to come up with research results that have practical significance in guiding China's green and sustainable development.

6. Conclusions

Based on DMSP/OLS and NPP/VIIRS nighttime light data, carbon emission data derived from the CEADs, and statistical yearbook data, the spatial and temporal features of the urban expansion and carbon emissions in the YRDUA from 2000 to 2020 were analyzed, and the spatial and temporal evolution of the relationship between the two was explored. The main conclusions obtained from this study are as follows:

(1) Between 2000 and 2020, the built-up area in the YRDUA continued to expand, and the cities along the Yangtze River were linearly distributed and developed along the east-west orientation. In particular, in the southern part of the Yangtze River region, Shanghai, Suzhou, Wuxi, and Changzhou developed rapidly. In addition, Hangzhou and Hefei, as provincial capital cities, had relatively high levels of land urbanization. According to the four sub-periods defined in this study, there were significant differences in urban expansion within the study area. The cities with the fastest expansion during periods 2000–2005, 2005–2010, 2010–2015, and 2015–2020 were Nanjing, Ningbo, Suzhou, and Shanghai, respectively.

(2) Based on the total value of nighttime light and carbon emissions from 2000 to 2020, a retrieval model was constructed, and the obtained linear regression equation had a goodness of fit of 0.92. It can be seen that the use of nighttime light data can effectively estimate the total carbon emissions of the cities within the study area, making up for the lack of statistical information for some areas and the difficulty of ensuring the continuity of years. On the whole, the carbon emission intensity in the YRDUA has exhibited a decreasing trend, with a larger reduction achieved during the period from 2005 to 2010 than during the other three sub-periods. This is mainly due to the progress of science and technology and the adjustment of the industrial structure.

(3) There was a significant correlation between the urban expansion and carbon emissions in the study area, and the synergistic expansion index between the urban expansion and carbon emissions of the YRDUA in each sub-period from 2000 to 2020 was strong or weak. However, the overall synergistic expansion index was 0.36, indicating a significant synergistic expansion relationship between the two. Decoupling analysis based on the growth elasticity changes revealed that the study area shifted from expansion negative decoupling to weak decoupling and strong decoupling. By 2020, 70% of the cities in the study area were in a decoupling state, and 30% had reached the best state of strong decoupling. It can be seen that the urban expansion in the study area contributed to the increase of carbon emissions, but there was a decoupling phenomenon.

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