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RESEARCH ARTICLE

Dynamic evolutionary characteristics and influence mechanisms of carbon emission intensity in counties of the Yangtze River Delta, China

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Abstract
Clarifying the intrinsic mechanism of county carbon emission intensity (CEI) is essential for guiding the realization of a low-carbon economy as well as for the strategic goals of carbon peaking and carbon neutrality. However, at present, scholars mostly focus on provincial and city scales, with the identification of influencing factors and spatial effect mechanisms of CEI rarely included in the analysis framework. Herein, with the help of three spatial weight matrices, the spatial autocorrelation, the "F + S" influence factor identification method, and the spatial panel econometric model were used to analyze the evolutionary paths and influencing factors of CEI for 209 counties in the Yangtze River Delta (YRD) from 2007 to 2020. The results show that (1) the CEI of the YRD decreased from 1.998t/10^4 RMB to 0.858t/10^4 RMB. Furthermore, the spatial pattern was low in the southeast and high in the northwest, with high-value areas concentrated in municipal districts and resource-based counties. (2) Moran's I spatial autocorrelation index indicated significant spatial clustering of county CEI. (3) Financial science and technology expenditure, industrial structure, share of urban built-up land, and the urban–rural income gap affected the change in CEI and its spatial effect, whereas total imports and exports had a significant negative effect on local CEI. Therefore, to achieve China's "double carbon" goal, it is necessary to consider the five development concepts as the core, strengthen inter-county exchanges and collaboration, as well as promote collaborative management of the ecological environment.

Keywords Carbon emission intensity · Spatial autocorrelation · Spatial panel econometric model · Yangtze River Delta counties

Introduction

Over the past few decades, China's rapid economic growth, urbanization, and industrialization have increased the demand for energy, surpassing the USA as the world's top CO_2 producer (Li et al. 2016). Excessive CO_2 emissions cause global warming and endanger human health, and China, as the "world factory," is experiencing international pressure to reduce emissions (Tang et al. 2022). Carbon emission intensity (CEI) reflects the carbon emissions generated per unit of GDP, serving as an important indicator of energy use and carbon efficiency of a country or region, of particular relevance for developing countries (Jotzo and Pezzey 2007). Statistics from the World Bank's WDI database show that the average value of China's CEI during the 2007–2020 period was 11.117t/10^4 dollars, approximately four times that of the USA and Japan as well as more than six times that of major developed countries in the European Union. The Yangtze River Delta (YRD) is the core area of China's economy and an important region reflecting national competitiveness. Thus, its green integration has been elevated to a national strategy, but, at the same time, the region also constitutes the most concentrated area of energy consumption in China (Zhang et al. 2022). Therefore,

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identifying the key factors influencing the CEI in the YRD and devising emission reduction strategies is of considerable theoretical and practical significance for guiding the development of China's low-carbon economy as well as the realization of carbon peaking and carbon neutrality strategic goals.

In recent years, many scholars have explored the spatial and temporal patterns of the CEI at different spatial scales (Sun and Huang 2022). Most existing studies have focused on macroscopic scales, i.e., national, provincial, and city scales (Chang and Chang 2016; Wang and Zheng 2021). Wang and Zheng (2021) found that, in the period from 2005 to 2017, China's CEI gradually decreased from east to west and from south to north, showing an aggregation effect in the inter-provincial spaces that gradually diminished. Zheng et al. (2018) conducted a survey of 333 cities in China, obtaining an average value of CEI across cities at 0.84 kg/dollars in 2013, with individual cities showing considerable variation(0.09–7.86 kg/dollars). At the microscale, data on county carbon emissions are still limited, owing to the influence of methodology, time span, and geographic coverage (Li et al. 2021). However, it is worth noting that in China, industrial sectors are the usual target of carbon emission reduction policies issued by provinces, an approach which largely ignores the administrative effectiveness and spatial heterogeneity of counties in reducing emissions in concert with their distinctive or leading industries (Qi et al. 2022).

To better understand the influencing factors and driving mechanisms of CEI, scholars have mainly employed index decomposition analysis (IDA), structural decomposition analysis (SDA), and nonparametric distance decomposition analysis (NDA) to explore the former (Bhattacharyya and Matsumura 2010; Jeong and Kim 2013). Bhattacharyya and Matsumura (2010) used the LMDI approach to investigate factors influencing carbon intensity in the EU-15 and concluded that the key factor contributing to its decline was energy intensity. Scholars have also worked on spatial measures based on IPAT or STIRPAT models (Cheng et al. 2014; Long et al. 2015). Cheng et al. (2014) used a spatial panel measurement model and found that the energy structure, industrial structure, and urbanization rate affected the evolution pattern of China's CEI. While these studies have demonstrated that the key influencing factors of CEI cover multiple dimensions and levels of the socioeconomic system, a systemic, holistic approach in the identification process is currently missing. Moreover, studies have ignored the notion that CEI is the joint result of the dynamic spatial effects of a county and its neighbors, thus paying little attention to the synergistic management of multiple subjects and factors (Song et al. 2020).

Based on the aforementioned findings, this study evaluated the spatial and temporal evolution as well as the spatial effects of CEI in 209 counties in the YRD from 2007 to 2020, quantitatively dissecting socioeconomic factors. This study has three innovative aspects: (1) research on the CEI was downscaled to the county level, which compensates for the lack of research at the micro-scale; (2) the "F + S" county CEI key factor identification method was constructed based on the five development concepts and the STIRPAT model, making the identification results more comprehensive and forward-looking than those in the literature; and (3) three spatial weight matrices (i.e., of geography, economy, and geo-economics) were created; the spatial spillover effect of CEI in the YRD counties was estimated by a spatial panel measurement model, and the partial differential decomposition method was used to explore the direct effect and spillover effect of each driver.

Materials and methods

Research area

The YRD is located at the "T"-shaped intersection (114°54′–122°12′E, 27°02′–35°08′N) along the river and coast of China, comprising Shanghai, Jiangsu, Zhejiang, and Anhui (Fig. 1). It is one of the country's most economically active, densely populated, and industrialized regions. In 2020, the GDP of the YRD accounted for more than 24.302% of the national total, with extremely active sectors including energy, industry, transportation, and construction. Rapid industrialization and urbanization in the region have considerably promoted the greenhouse effect. The CEI in the YRD is characterized by a center-periphery layout, cross-border transmission, and boundary expansion. County studies are essential to understanding regional heterogeneity and formulating effective carbon reduction policies. To promote the planning and construction of low-carbon eco-cities in counties of the YRD, this study used the 2007 administrative division as its basis, merged and edited the county boundaries and data, and finally selecting a total of 209 county units in 42 municipal districts and 167 counties as the research objects.

Data sources

The Open Data Inventory for Anthropogenic Carbon Dioxide (ODIAC) published by the Universities Space Research Association (USRA) (https://db.cger.nies.go.jp/dataset/ODIAC/) is widely used by scholars for studies of carbon emission at the microscopic scale. The dataset is a high-spatial-resolution (1000 m) gridded monthly scale data product obtained by further downscaling based on fossil fuel data, combined with power plant and night-time light data, having a simulation accuracy of over 80% (Oda et al. 2018). The urban built-up land data were

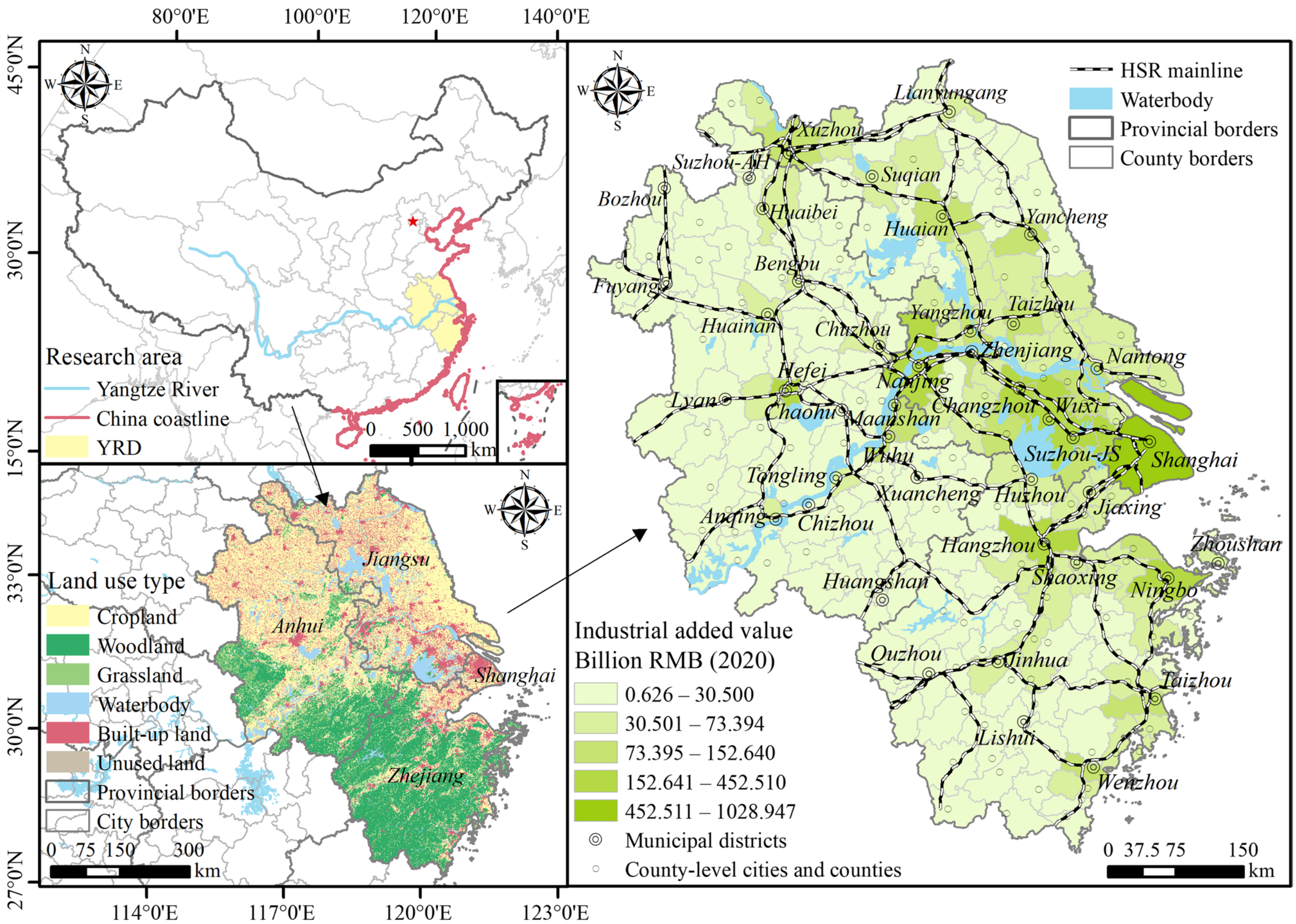

Fig. 1 Location, urbanization, and industrialization of the YRD

replaced with impervious surface remote sensing monitoring results derived from the annual China Land Cover Dataset (CLCD) published by Wuhan University (https://zenodo.org/record/5816591). Thematic data raster products were obtained through year-by-year classification using time-series Landsat image data with a spatial resolution of 30 m and an average accuracy greater than 80% (Yang and Huang 2021). The high-speed railway (HSR) number data were based on Python crawler technology to obtain train schedules from the China Railway Customer Service Center (https://www.12306.cn), and the original data were further processed, handled, and parsed to obtain the final result (Wang et al. 2018). The remaining socioeconomic data were derived from the China County Statistical Yearbook and the statistical yearbooks of the relevant provinces, cities, and counties. Owing to the change in the statistical caliber of financial science and technology expenditures caused by the reform of the government revenue and expenditure classification system and considering the start of the operation of China's HSR, the study period was finally set to 14 years: from 2007 to 2020.

Research methods

Spatial autocorrelation

Spatial autocorrelation is an inherent spatial property that can be used to test for significant spatial clustering or the spillover of elemental property values (Anselin 1995). This study not only interprets the spatiotemporal variation characteristics of the CEI, but also provides a necessary condition for the correct setting of the spatial panel model. Therefore, global and local spatial autocorrelations were used to characterize the spatial clustering of CEI.

(1) Global spatial autocorrelation (global Moran's I): Reflecting the average degree of correlation and its significance among all geographical units in the region, it can reveal the spatial distribution of the CEI in a county as a whole.
(2) Local spatial autocorrelation (local Moran's I): This mainly describes the spatial agglomeration phenomenon around each geographical unit with similar-level

units and the spatial divergence phenomenon between each unit and neighboring units at a level, which can identify the spatial agglomeration pattern of the CEI in the county and detect the existence of spatial heterogeneity.

Spatial econometric models

(1) Spatial weight matrix construction. To detect the spatial correlation characteristics of the CEI more comprehensively than in the literature and to set the spatial panel model correctly, we employed three spatial weight matrices (Zeng et al. 2019). The first is the geospatial weight matrix (W_g), which uses the latitudes and longitudes of counties in order to calculate the reciprocal representation of their distance. The second is the economic distance weight matrix (W_e), represented by the reciprocal of the absolute difference between the average per capita income of counties *i* and *j*, considering the possible spatial correlation among the counties' economies. The third is the geographic-economic weight matrix (W_n), a nested matrix of geographic and economic weights that can more comprehensively and objectively reflect the spatial correlation pattern of the CEI in the county, where $W_n = 0.5 \times (W_g + W_e)$, meaning that the geospatial weight is equal to the economic distance weight (Zhang et al. 2020).

(2) Spatial panel econometric model settings. Spatial econometric models can incorporate spatial effects and can be used to identify spatial interactions between geo-

$$\left[\frac{\partial y}{\partial x_{1k}} \cdots \frac{\partial y}{\partial x_{nk}}\right] = \begin{bmatrix} \frac{\partial y_1}{\partial x_{1k}} & \cdots & \frac{\partial y_1}{\partial x_{nk}} \\ \vdots & \vdots & \vdots \\ \frac{\partial y_n}{\partial x_{1k}} & \cdots & \frac{\partial y_n}{\partial x_{nk}} \end{bmatrix} = (i - \rho w)^{-1} \begin{bmatrix} \beta_k & w_{12}\theta_k & \cdots & w_1\theta_k \\ w_{21}\theta & \beta_k & \cdots & w_{21}\theta_k \\ \vdots & \vdots & \vdots & \vdots \\ w_{1n}\theta_k & w_{n2}\theta_k & \cdots & \beta_k \end{bmatrix} \tag{5}$$

spatial units. At this stage, there are three widely used and mature settings, describes hereafter (Hao et al. 2016; Lv et al. 2022).

① The spatial lag model (*SLM*) describes the substantive spatial correlation, and the spatial effect mainly exists in the econometric model setting in the form of the response variable lag, that is

$$y_{it} = \rho \sum_{j=1}^{n} w_{ij} y_{it} + \beta x_{it} + \mu_i + \upsilon_t + \varepsilon_{it} \tag{1}$$

② The spatial error model (*SEM*) describes the spatial disturbance correlation, and the spatial effect mainly exists in the measurement model setting in the form of error lag, that is

$$y_{it} = \beta x_{it} + \mu_i + \upsilon_i + \mu_{iy}, \mu_{it} = \lambda \sum_{j=1}^{n} w_{ij} \mu_{it} + \varepsilon_{it} \tag{2}$$

③ The spatial Durbin model (*SDM*) incorporates the spatial effects of the response and explanatory variables in the econometric model setting in the form of

$$y_{it} = \rho \sum_{j=1}^{n} w_{ij} y_{it} + \beta x_{it} + \theta \sum_{j=1}^{n} w_{ij} x_{it} + \mu_i + \upsilon_t + \varepsilon_{it} \tag{3}$$

where y_{it} is the observed value of the response variable; x_{it} is the observed value of the explanatory variable; ρ is the spatial regression coefficient of the response variable; λ is the spatial regression coefficient of the error term; θ is the spatial regression coefficient of the explanatory variable; β is the regression coefficient of the explanatory variable; υ_t and μ_i denote temporal and spatial fixed effects, respectively; ε_{it} is a random error term obeying an independent identical distribution, indicating other factors not included in the econometric model; and w_{ij} is the spatial weight matrix.

(3) Spatial effect decomposition. Lesage and Pace (2009) pointed out that partial differential methods should be applied in the context of cross-sectional models to test the direct and spillover effects of variables (Lesage and Pace 2009). Therefore, the SDM shift term is organized in the following general form:

$$Y = (i - \rho w)^{-1} a l_n + (i - \rho w)^{-1}(x\beta + wx\theta) + (i - \rho w)^{-1}\varepsilon \tag{4}$$

where is the partial differential decomposition matrix of response variable *y* with respect to the *k*th explanatory variable.

where the direct effect is the average of the main diagonal elements of the right-hand matrix, which reflects the marginal effect of the *k*th variable of the cross-sectional cell on the dependent variable. The spillover effect is the average of elements other than the main diagonal and reflects the marginal effect of the *k*th variable of the cross-sectional cell on the dependent variable of other cells, or the effect of the *k*th variable of all other cross-sectional cells on the dependent variable of one cell.

Variable selection

To measure the influence of socioeconomic factors on CEI more comprehensively than in the literature, this study constructed the "F + S" method to identify the key factors of CEI in counties, drawing on the literature (Li et al. 2021;

Wang and Zheng 2021). "F" refers to the five development concepts, which run through all areas of economic and social development: innovation, coordination, green, open, and shared development (Liu et al. 2021). "S" refers to the improved STIRPAT model based on the IPAT model, which assumes that the environmental pressure caused by human activities is mainly affected by population, affluence, and technological progress. Table 1 lists the specific variables.

To achieve the aim of this research, this study sets *CEI* as the response variable. The core explanatory variables are as follows. (1) Innovation development (*I-DEV*): The degree of government attention to innovation is an important determinant of a city's innovation capacity, and financial science and technology expenditures are important indicators of this capacity (Zhang et al. 2020). (2) Coordinated development (*C-DEV*): Promoting the coordinated development of the three industries is an urgent need for the current low-carbon economy. The industrial structure is the basic expression of the coordinated development of industries, using the ratio of the output value of the secondary industry to GDP (Gao et al. 2022). (3) Green development (*G-DEV*): Driven by the dual-wheel drive of industrialization and urbanization, the disadvantages of disorderly expansion of the urban scale appear and are restricted by many problems, such as a shortage of land resources and low utilization efficiency. Therefore, a reasonable land-use method is the green development of the YRD. Therefore, it is represented by the proportion of urban built-up land area to the total area (Liu et al. 2022). (4) Open development (*O-DEV*): An open economy is essentially a process of economic and trade liberalization, wherein total imports and exports can reflect the end result of this process (Tian et al. 2022). (5) Shared development (*S-DEV*): Shared development aims to solve the contradiction between unbalanced and insufficient development, with this imbalance being most obvious in urban and rural areas. Thus, this study used the urban–rural per capita income gap as a measure (Pearce and Kingham 2008).

Using the STIRPAT model and theory, the affluence level, population agglomeration, as well as traffic and transportation were set as the control variables. Referring to the environmental Kuznets theory, there is a nonlinear relationship between per-capita income and environmental pollution, with the affluence level (*AL*) characterized by per-capita GDP (Sun 1999). Population agglomeration (*PA*) affects CEI through scale and agglomeration effects or agglomeration diseconomies; the former and latter cause CEI to decrease and increase, respectively (York et al. 2003). In transportation (*T*), HSR is one of the most effective public means of emission reduction, and, as the number of high-speed rail trips increases, exhaust emissions from motor vehicles and CEI decrease (Pomykala and Szelag 2022). In addition, to make the data more consistent with a normal distribution and eliminate model heteroskedasticity, we performed a logarithmic transformation on all variables before regression.

Results

Spatiotemporal evolution characteristics of CEI

Chronological evolution characteristics

From 2007 to 2020, the CEI of the YRD generally showed a decreasing trend, with greatest efforts toward energy conservation and emission reduction in China. However, the emission reduction effectiveness was far behind that of the major developed countries (Fig. 2). The CEI of the YRD decreases from 1.998t/10^4 RMB in 2007 to 0.858t/10^4 RMB in 2020, with an annual average CEI of 1.35t/10^4 RMB and an average annual decline rate of 6.277%. The annual average intensity is slightly lower than that of China as a whole (1.653t/10^4 RMB), but the gap is still large compared with the USA (0.47t/10^4 RMB), Germany (0.317t/10^4 RMB), and Japan (0.363t/10^4 RMB).

To understand the distribution of CEI in counties from 2007 to 2020 more intuitively, we used MATLAB 2020b software to draw a 3D kernel density estimate (Fig. 2). The

Table 1 Factors affecting the CEI of the YRD counties

Variable Name	Variable Explanation	Unit	Symbol
Carbon emission intensity	Carbon emission to GDP ratio	t/10,000RMB	*CEI*
Innovative development	Financial science and technology expenditure	10,000RMB	*I-DEV*
Coordinated development	Secondary industry output value to GDP	%	*C-DEV*
Green development	Urban built-up land area to total area	%	*G-DEV*
Open development	Total import and export	10,000RMB	*O-DEV*
Shared development	Per capita income disparity between urban and rural	RMB	*S-DEV*
Affluence level	Per capita GDP	RMB	*AL*
Population agglomeration	Population density	Persons/km^2	*PA*
Traffic and transportation	Number of high-speed railways	Time	*T*

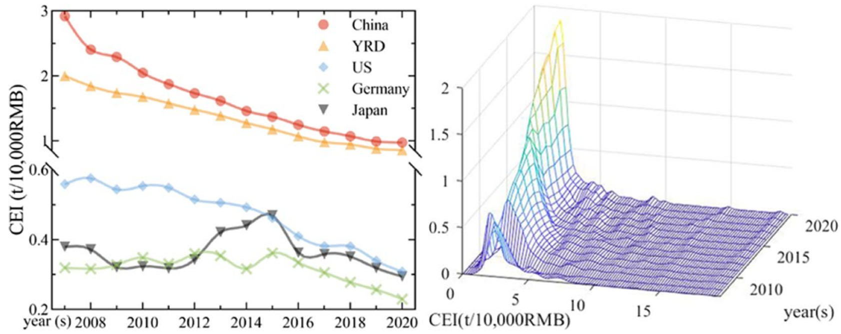

Fig. 2 Time series characteristics and kernel density distribution of CEI in YRD

CEI at the county level shows a trend of a positively skewed distribution, and the kernel density curve shifts from "short and sturdy" to "tall and picky," showing the characteristics of a single-peak distribution, with the peak gradually moving to the left. This result indicates that the overall CEI of the YRD is decreasing, and the high-intensity counties are decreasing faster than the low-intensity counties, gradually forming a "club convergence" effect from high values to low values, namely, the "convergence effect." In turn, this indicates that the government's "emission reduction" measures are effective. From 2011 to 2020, the right tail of the curve extends outward, indicating that a small number of highly intensive counties are still to achieve the reduction target, and the gap with other counties is gradually widening.

Spatial evolution characteristics

To analyze the spatial evolution characteristics of the CEI in the YRD counties, 4 years (2007, 2010, 2015, and 2020) were selected for visualization (Fig. 3), and the CEI was divided into five classes according to the mean-standard deviation method (Long et al. 2012).

The CEI of counties in the YRD varied widely, with an overall spatial pattern of low CEI in the southeast and high CEI in the northwest. The high-value areas were mainly concentrated in municipal districts and resource-based counties (Long et al. 2021). For example, the Tongling Municipal District has long been dominated by the non-ferrous metal industry, where smelting produces a large amount of CO_2, making the contribution of high-carbon industries to the GDP high. The "high carbon ridge belt" along the Yangtze River is gradually "fading." Since the end of the twentieth century, the aim of constructing the Yangtze River Industrial Belt has been to promote key industrial and infrastructure development in cities along the river, resulting in rapid economic development. In recent years, under the strategy of Yangtze River protection, the problem of the "chemical industry surrounding the river" has been alleviated as has the greenhouse effect in counties along the river, with the CEI being rapidly reduced (Sun et al. 2018). The center of gravity "south into the north back" characteristics are evident. During the study period, the major decreases in CEI were in Huainan Municipal District, Suixi County, and Huaiyuan County in Anhui Province, with the minor decreases concentrated in the Shengsi, Dongtou, and Daishan counties in Zhejiang Province. The standard deviation ellipse statistics module indicated that the center of gravity of the CEI at the county level generally shifted from northwest to southeast, with an average annual shift of 2.273 km. This phenomenon indicates that the industrial and energy consumption structures of some high-CEI counties in the Anhui and northern Jiangsu Provinces have been substantially improved. Thus, the benefits of implementing air pollution prevention and control policies are now evident (Wang et al. 2022).

Spatial effects of CEI

Neither the kernel density estimation nor the standard deviation ellipses considered the spatial correlation of the data. Thus, we examined global and local autocorrelations based on three spatial weights (W_g, W_e, and W_n) using GraphPad software and stata14.0 software.

Global spatial autocorrelation

The CEI of counties in the YRD showed significant spatial clustering and positive spatial correlation (Fig. 4). Moran's I values for all three spatial weight matrices were greater than 0, and the *P*-values were less than 1%. The spatial agglomeration of W_e and W_n gradually increased, but the agglomeration of W_g weakened. According to Tobler's first law of geography, geographical objects or attributes are correlated in a spatial distribution, and there are agglomerative, random, and regular distributions (Tobler 1970). Moran's I values for W_g exhibited a significant positive correlation, and the Z value fluctuated slightly, indicating that the influence of geographical factors is relatively stable. This also verifies that geographical spatial distance is an important basis for the spatial effect of CEI. The influence of economic factors was more significant than that of geographical factors, and the average Moran's I value for W_e was the highest (0.25),

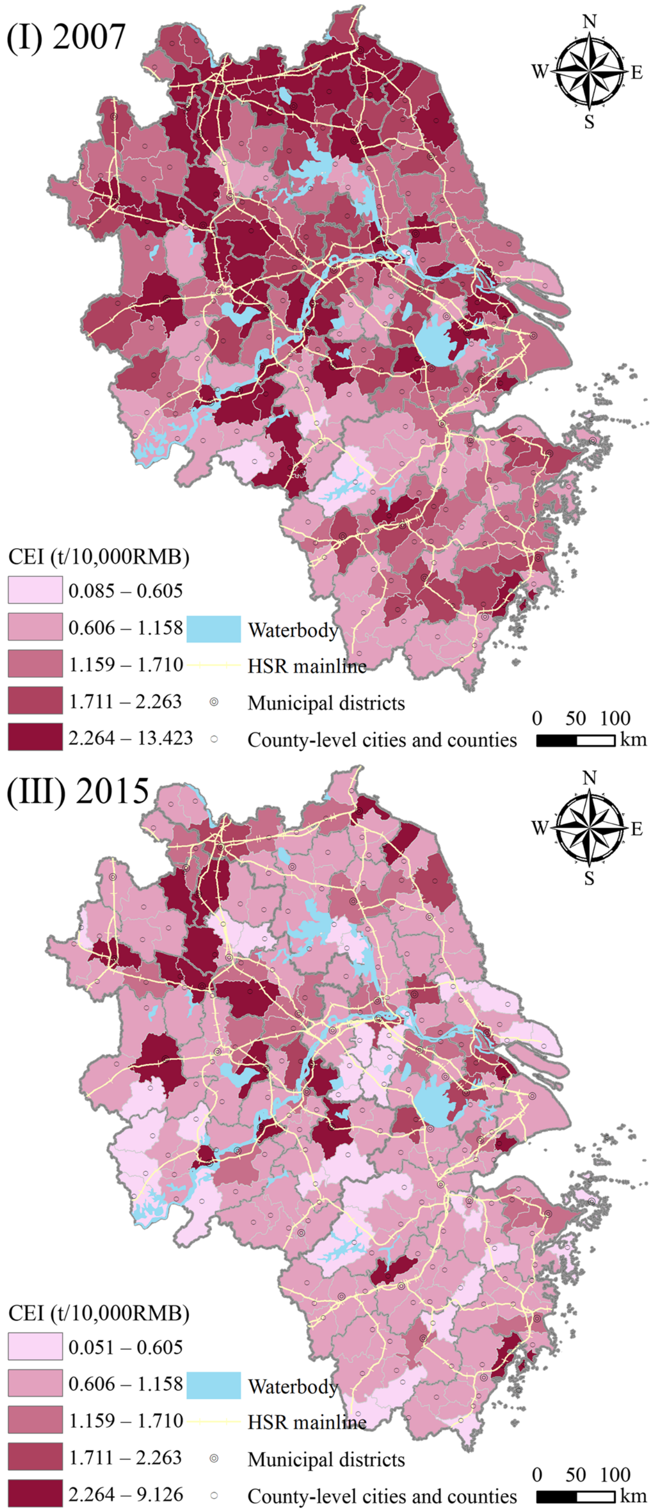

Fig. 3 Spatial distribution of CEI in YRD

indicating that the coupled correlation between CEI and economic factors was high. The growth rate of the national economy is much faster than that of carbon emissions generated by transportation development, energy consumption, and land-use changes. Therefore, economic differences largely determine those in CEI. W_n corroborates the important influence of the interaction between geographic and economic factors on CEI.

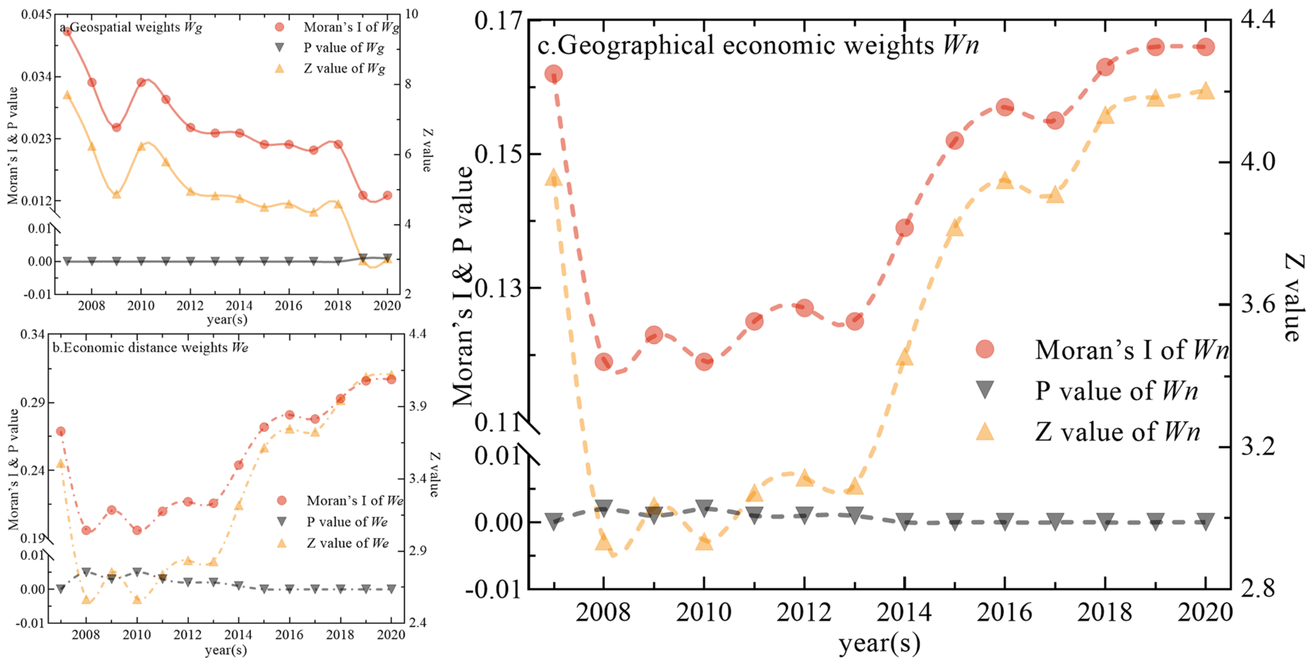

Fig. 4 Moran's I value of CEI in YRD

Local spatial autocorrelation

Four representative years (2007, 2010, 2015, and 2020) were selected, and the results of the CEI scatter plot for YRD counties based on W_n are shown in Table 2.

The CEI exhibited obvious clustering characteristics. The average proportion of counties in the first and third quadrants was 66.029%, indicating an overall spatial aggregation trend of H–H and L-L and a significant spatial spillover effect within the region. The number of counties in the hot spot and cold spot areas fluctuated down and up, respectively. Among them, the hot spots were mainly located in northern and eastern Anhui, that is, the Suzhou, Huainan, and Chuzhou municipal districts, as well as in northern and central Jiangsu, i.e., Xuzhou Municipal District, Lianyungang Municipal District, and Yizheng County. During the "12th 5-year plan" and "13th 5-year plan," Jiangsu Province actively implemented administrative, economic, and legal measures to prevent and mitigate the impact of energy production and use on the environment, leaving only the area north of the Yangtze River in Anhui Province with significantly high CEI "club" characteristics after 2015. The cold spots were mainly distributed in western Anhui, southern Anhui, southern Jiangsu, and most of the counties in Zhejiang Province.

Factors and mechanisms influencing CEI

Spatial econometric model testing and selection

First, the Lagrange multiplier (*LM*) test statistic was used to determine whether the *SLM* or *SEM* were better than the non-spatial effects model (Elhorst 2010). The aim was to use *OLS* to estimate a constrained model that does not consider the spatial effect and then combine the relevant information of the *OLS* estimation into the LM_{SLM}, robust LM_{SLM}, LM_{SEM}, and robust LM_{SEM} formulas by combining the three spatial weight matrices (Elhorst 2012). The results show that the *LM* test results rejected the original hypothesis, indicating that the spatial effect model was better at characterizing the data than the non-spatial effect model. Second, because the *LM* test shows that one or both of the *SLM* and *SEM* models hold, the *SDM* should be further considered (Lesage and Pace 2009). Finally, the likelihood ratio (*LR*) test result (3446.53, $p = 0.000$) for the null hypothesis that spatial fixed effects are jointly significant indicates that the two-way fixed effects outperform the spatial fixed effects. Another *LR* test result (13.28, $p = 0.000$) indicates that the null hypothesis that temporal fixed effects are jointly significant is invalid. Accordingly, this study selected nested temporal and spatial bidirectional fixed *SDM* for analysis.

Because the model contained spatially lagged response variables, the maximum likelihood (*ML*) method was used to obtain unbiased and consistent estimation results (Table 3) (Lee and Yu 2010). The estimation results for W_g, W_e, and W_n were highly consistent and passed the significance test. The estimation results for W_n were selected for subsequent analyses (Ye et al. 2018). The spatially weighted term $w \times \ln CEI$ of CEI is significantly positive, which indicates that the CEI of the target counties is significantly influenced by the CEI of neighboring counties, that is, the

Table 2 Local autocorrelation test results

Type	Year				Average of proportions (%)
	2007	2010	2015	2020	
First quadrant	32 (7)	27 (5)	20 (5)	16 (6)	11.364 (2.751)
Second quadrant	33 (1)	39 (1)	39 (1)	38 (1)	17.823 (0.478)
Third quadrant	114 (0)	109 (0)	115 (0)	119 (0)	54.665(0.000)
Fourth quadrant	30 (1)	34 (2)	35 (1)	36 (0)	16.148 (0.478)
Total	209 (9)	209 (8)	209 (7)	209 (7)	100.000 (3.708)

Results of the clustering distribution of the LISA plots that passed the significance test are shown in parentheses

Table 3 Regression results of SDM

	W_g		W_e		W_n	
	Coefficient	*Z* value	Coefficient	*Z* value	Coefficient	*Z* value
ln*I-DEV*	0.009**	2.34	0.011***	3.11	0.010***	2.85
ln*C-DEV*	0.004	0.23	0.006	0.46	0.005	0.35
ln*G-DEV*	−0.003	−0.08	0.072**	2.28	0.065**	2.01
ln*O-DEV*	0.003	0.83	0.004	0.93	0.003	0.72
ln*S-DEV*	−0.065***	−2.99	−0.083***	−4.36	−0.086***	−4.40
ln*AL*	−0.936***	−54.75	−0.937***	−59.73	−0.940***	−58.97
ln*PA*	−1.005***	−25.61	−0.998***	−27.22	−1.002***	−27.04
ln*T*	−0.004**	−2.36	−0.005***	−2.69	−0.004**	−2.52
$w\times$ln*I-DEV*	0.089**	2.36	0.001	0.28	0.003	0.43
$w\times$ln*C-DEV*	0.255**	2.07	0.040***	3.16	0.073***	3.22
$w\times$ln*G-DEV*	0.968***	3.69	0.030	0.90	0.081	1.38
$w\times$ln*O-DEV*	−0.039	−0.83	0.002	0.45	0.004	0.58
$w\times$ln*S-DEV*	−0.142	−1.01	0.074***	3.58	0.121***	3.36
$w\times$ln*AL*	1.048***	6.70	0.299***	14.72	0.530***	14.71
$w\times$ln*PA*	1.184***	3.62	0.327***	7.75	0.593***	7.79
$w\times$ln*T*	0.012	0.65	0.004**	2.41	0.008**	2.35
$w\times$ln*CEI*	0.725***	10.80	0.265***	18.74	0.475***	18.81
R-squared	0.684		0.905		0.909	
Log-likelihood	3151.481		3242.843		3245.937	
Obs	2926		2926		2926	

*$P<0.1$, **$P<0.05$, ***$P<0.01$

CEI of the YRD counties has a positive "spillover effect." In general, although the *SDM* provides estimates of two-way fixed effects, it is difficult to accurately measure the direct effects of the independent variables on the dependent variable because they do not directly reflect their marginal effects (Lesage and Pace 2009). Therefore, the direct and spillover effects of the respective variables were calculated using partial differential equations (Table 4).

Spatial effect decomposition

The growth of local financial science and technology expenditure induces an increase in the local CEI, which is consistent with the findings of Chen et al. (2020), and increases the CEI of neighboring regions through spillover effects. In general, technological advances reduce the CEI mainly through the development of clean energy or by increasing energy-use efficiency, that is, by reducing fossil fuel consumption while producing the same GDP (Wang et al. 2019). In contrast, there is a positive relationship between local financial science and technology expenditures and local CEI. Technological innovation stimulates local economic activity and increases energy consumption, offsetting energy savings due to efficiency gains. In contrast, this may be related to inadequate investment in financial science and technology expenditures for research and the development of major energy-saving technologies as well as the training of energy management talents. Local financial

Table 4 Estimated results of direct effects and spillover effects

	Direct effect		Indirect effect		Total effect	
	Coefficient	*Z* value	Coefficient	*Z* value	Coefficient	*Z* value
ln*I-DEV*	0.011***	2.93	0.015*	1.88	0.026*	1.90
ln*C-DEV*	0.010*	1.63	0.139***	3.30	0.149***	3.10
ln*G-DEV*	0.077**	2.54	0.198**	2.27	0.275***	3.10
ln*O-DEV*	−0.003*	1.84	0.017	0.79	0.014	0.94
ln*S-DEV*	−0.079***	−4.17	0.146**	2.38	0.066	1.03
ln*AL*	−0.933***	−60.07	0.150***	3.08	−0.783***	−15.52
ln*PA*	−0.993***	−26.47	0.207*	1.67	−0.786***	−5.88
ln*T*	−0.004**	−2.51	0.011*	1.84	0.007	1.17

science and technology expenditures have a spillover effect on regional innovation in neighboring areas, causing neighboring governments to increase their financial investments in science and technology in order to obtain dividends under the dual promotion of demonstration and driving effects (Huang et al. 2022). In 2020, the YRD accounted for 50% of the top 100 counties in the country, with industrial development zones as well as science and technology parks being established, which had a siphon effect on the flow of production factors, such as capital and manpower, in the central and western regions, increasing their economic vitality and the consumer demand for energy.

An increase in the share of local secondary industries will in turn increase the local CEI, contributing to the CEI of neighboring regions. Most studies have concluded that industrial structure is a driver of CEI growth, mainly because of the irrational internal structure of the secondary industry, with high energy consumption, high emissions, inefficient industries, and strong energy dependence (Gao et al. 2022). The model results verify the view that every 1% positive change in the share of secondary industry leads to a 0.01% increase in the local CEI. In the study sample, the number of counties with secondary industries accounting for more than 45% of the GDP from 2007 to 2020 amounted to 58.852% of all counties, and the industrial structure of counties in the YRD region remained dominated by secondary, tertiary, and primary industries. In recent years, industrial structure optimization and upgrading in the YRD have accelerated the development of modern service industries, with high-pollution and high-energy-consuming enterprises continuing to advance near the region. The spillover effect of the industrial structure is much greater than the direct effect, as each positive change of 1% leads to a 0.139% increase in the CEI of neighboring areas (Li et al. 2020). With the high-quality integrated development of the YRD and the deep integration of innovation and industrial chains, the influence of the share of secondary industry on CEI will gradually diminish.

An increase in the proportion of local urban built-up land had a significant positive effect on the CEI of both the local and neighboring regions. Urbanization is accompanied by an expansion of urban land and a shift in the type of use, changing the urban carbon sink and carbon cycle process. Urban land development, including infrastructure and building construction, also results increases energy demands (Zhang et al. 2021). Our results show that for every 1% increase in the proportion of local urban built-up land, the local CEI increased by 0.077%. With the implementation of China's new round of the "reduction" policy of low-efficiency built-up land in 2016, such as Shanghai's use of 3200 km^2 as the "final scale" of planned built-up land, the relationship between future built-up land expansion and CEI will enter a stage of qualitative change. In most cities, land expansion has a weak inhibitory effect on that in neighboring cities. However, owing to improved accessibility, it can drive land expansion in cities that are a certain distance away (Wu et al. 2020). Moreover, city land expansion also increases the complexity of urban spatial patterns, which reduces the efficiency of motor vehicle travel and increases the CEI (Hong et al. 2022).

Total imports and exports suppressed the local CEI and passed the 10% significance test but did not significantly affect the CEI of neighboring regions. These results suggest that import and export trade can help China reduce carbon emissions, indicating that the "pollution haven" hypothesis is not valid. On the import side, the YRD mainly benefits from absorbing and learning from the low-carbon technologies of developed countries and raising the environmental access threshold for enterprises. On the export side, due to pressure from international public opinion, counties of the YRD have adjusted export tax rebates, imposed export tariffs, reduced export quotas, and implemented other means to limit the export of high-energy-consuming, high-polluting products, of which steel products are the most common. Total exports from Shanghai, Jiangsu, Zhejiang, and Anhui increased from 2007 to 2017, while steel exports declined by 0.938%, 0.827%, 0.387%, and 5.615%, respectively. To a certain extent, this result may indicate a gradual increase in "green exports," which is conducive to the reduction of local CEI (Cheng et al. 2014).

The local urban–rural income gap has negative and positive effects on the CEI of local and neighboring regions, respectively, with both passing the 10% significance test. Wang and Zhang (2021) found that economically developed regions in eastern China are prone to the phenomenon of "governance by the rich," which, together with the effects of consumption-investment transmission, gradually turns environmental governance from a luxury to a necessity. Therefore, the larger the local urban–rural income gap in the YRD, the more favorable this is for local carbon emission reduction. Generally, influenced by the rise of countryside enterprises and the rapid development of urbanization, more economically developed regions have a smaller urban–rural income gap, indicating that the urban–rural income gap in the counties surrounding the municipal district is larger than that in the municipal district itself. Under pressure from the income gap, local rural areas have a stronger claim to economic growth than to environmental protection. As a result, local governments may take the initiative to reduce environmental regulations, leading to a concentrated generation of pollution emissions.

Effect of each control variable on CEI. An increase in local GDP per capita suppressed local CEI and increased that in neighboring regions through negative spillover effects. The YRD is extremely close to the post-industrialization stage. Affluent regions were affected by the cost of land and pollution control costs, and the output value of the steel, non-ferrous metals, and petrochemical industries fell by 4.044%, 3.972%, and 1.963%, respectively. Local high-end manufacturing and equipment manufacturing industries are transforming into low-carbon versions, while the greenhouse effect is increasing in neighboring regions, which is consistent with the findings of Sun (1999). Increased local population density suppressed the local CEI and led to increased CEI in neighboring areas, which was consistent with the results of studies confirming that population size is an important driver of climate warming (Wang et al. 2019). Population density has two aspects (Liu et al. 2017). Locally, the agglomeration effect is predominant, with the county's population and activity clustering driving the construction of infrastructure and public utilities, as well as the formation of agglomeration economies, such as knowledge spillovers and human capital, increased labor productivity, and reduced energy consumption. Neighborhoods are dominated by agglomeration diseconomies, where the CEI has increased (Wang et al. 2019). An increase in the number of local HSR reduces the local CEI, but increases the neighboring regions' CEI. As a new mode of energy-efficient and environmentally friendly transportation, the HSR has had a substantial impact on high-pollution, energy-consuming road transportation. From 2008 to 2016, China's HSR network helped reduce up to 14.76 million tons of CO_2 (Schmutzler 2021). In addition, the increase in HSR trips compressed space–time

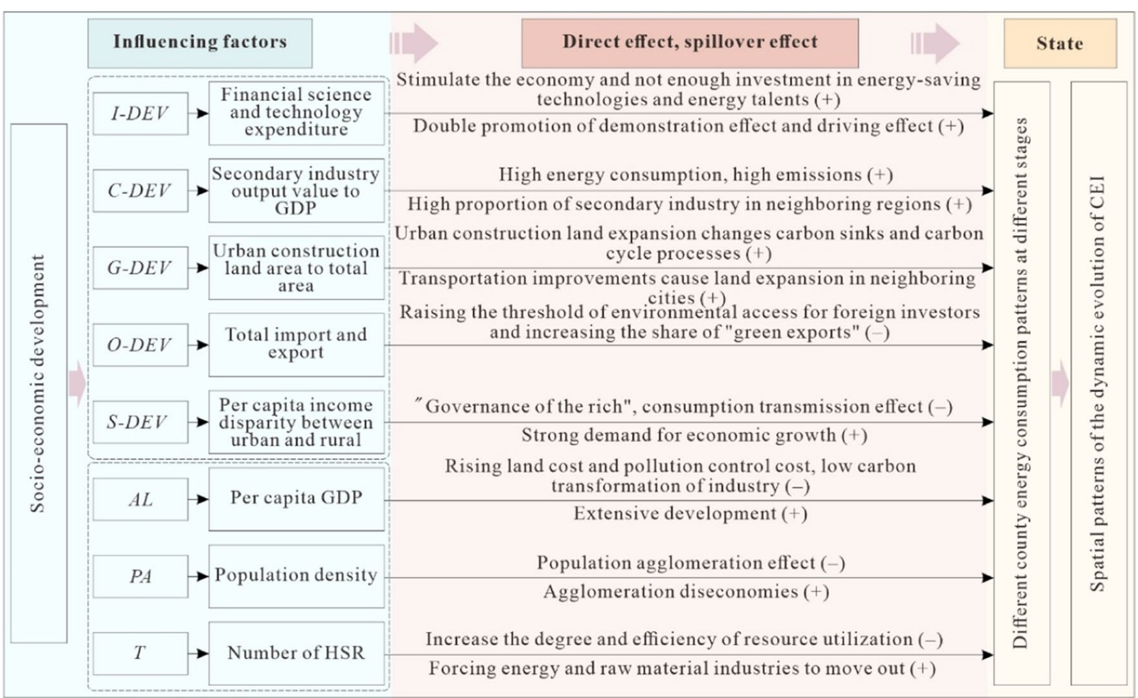

Fig. 5 Influence mechanism of CEI in YRD counties (the top of the arrow indicates the direct effect on local CEI, the bottom indicates the spillover effect, and the blank indicates the insignificant effect)

distances, accelerated the redistribution of factors, and enhanced the degree and efficiency of resource utilization, reducing the local CEI. The neighboring regions may be affected by the opening of the HSR, causing the local secondary industry to move to another location.

Based on Fig. 4, the mechanism of CEI influence under the interaction of direct and spillover effects is summarized (Fig. 5).

Discussion

In recent years, global warming caused by high CO_2 emissions and the resulting typhoons, rainstorms, droughts, as well as other natural disasters have become a growing concern for China's population and government (Tang et al. 2022). Studies on the internal mechanism determining the CEI in counties of the YRD can provide a scientific basis for special prevention and control, scenario simulation, as well as early warnings of CEI risks, in addition to internal industrial planning and high-quality development in the region (Liu et al. 2021).

The main recommendations based on the results of this study are as follows: (1) optimize the structure of scientific and technological expenditures, increase investment in low-carbon science and technology funds and energy management personnel training, explore the research and development of key bottleneck technologies, and establish a comprehensive interdisciplinary system to achieve the goals of energy conservation and emission reduction; (2) continuously promote the transformation and application of scientific and technological achievements, take the road of "science and innovation + industry," continuously optimize the industrial structure; accelerate the transformation of old and new dynamics, as well as create a highland of green, low-carbon, and cyclic development; (3) strengthen the protection of arable land and reduce the amount of inefficient built-up land to promote intensive urban development; (4) with regard to "one belt and one road" construction, accelerate the integration of customs clearance, build a higher level of open platform, raise the threshold of foreign investment in environmental access, increase the share of "green exports," and introduce clean energy technology; and (5) joint development of industry standards to control high energy consumption and emissions, achieve an ultralow emission transformation of the steel, cement, and fuel boilers industries, as well as promote collaborative ecological and environmental management.

While the above-described research results fill a knowledge gap within the literature, the current study does have some limitations. For example, owing to the frequent adjustment of administrative divisions within counties, changes in the statistical caliber of indicators, and the lack of microscale data, improvements are necessary in data quality and the selection of variables for measurement models. Further research can optimize the analysis of factors and mechanisms influencing the CEI in counties in terms of data precision and comprehensive indicators (Song et al. 2020). In addition, this study explored the main factors controlling the CEI in counties of the YRD with regard to human factors. Meanwhile, natural factors also have a significant influence on the CEI. It is therefore necessary to comprehensively explore the impact of natural geographical factors on the CEI during socioeconomic development and propose strategies for low-carbon development from the perspective of regional resource endowment, energy imports, exports, etc. (Mehmood et al. 2022).

Conclusions

The current study reveals the trends of change and regional differences in the CEI of counties in the YRD. Furthermore, we analyzed the evolution pattern of its spatial agglomeration, and, with the help of the "F + S" method, we used a spatial panel econometric model to clarify the main factors controlling county CEI of counties and further analyzed the mechanisms of influence. The main findings can be summarized as follows.

From 2007 to 2020, the CEI of the YRD counties decreased from 1.998t/10^4 RMB to 0.858t/10^4 RMB, but the effectiveness of emission reduction lagged far behind that of the world's major developed countries. The CEI showed a trend of positive skewed distribution and a significant "convergence effect." Spatially, the overall distribution pattern is low in the southeast and high in the northwest, with the high-value areas are mainly concentrated in municipal districts and resource-based counties. The "high carbon mid-ridge belt" along the Yangtze River shows gradual "fading" characteristics. The center of gravity "south into the north back" is apparent, with the industrial structure and energy consumption structure of some high CEI counties in Anhui and northern Jiangsu greatly improving as the implementation of air pollution prevention and control policies has shown initial results.

Under the three spatial weight matrices, Moran's I values were greater than 0 and passed the 1% significance test. The CEI of the YRD counties showed significant spatial clustering and a positive spatial correlation. The number of counties in hot and cold areas fluctuated down and up, respectively. After 2015, only counties north of the Yangtze River in Anhui Province showed significant high CEI "club" characteristics, and cold areas were mainly distributed in western Anhui, southern Anhui, southern Jiangsu, and the vast majority of counties in Zhejiang Province.

The CEI between counties in the YRD has a positive "spillover effect," and there is an urgent need to create a cross-regional joint prevention and control mechanism for pollution management. Financial science and technology expenditure, the proportion of secondary production, the proportion of urban built-up land, and urban–rural income gap have both direct and spillover effects on the CEI, as follows: financial science and technology expenditure, the proportion of secondary production, and the proportion of urban built-up land have positive effects on the CEI in local and neighboring regions; the urban–rural income gap has a significant negative effect on CEI in local areas, while the opposite is true for neighboring regions. Total imports and exports have a significant negative impact on local CEI, disproving the "pollution refuge" hypothesis. The control variables have heterogeneous effects on the CEI of counties in the YRD, with GDP per capita, population density, and HSR trips having significant negative effects on the local CEI and significant positive relationships with that in neighboring regions.

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Data availability The datasets used and/or analyzed in this study are available from the corresponding author upon reasonable request.

Declarations

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Consent for publication Not applicable.

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