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The Influencing Effects of Industrial Eco-Efficiency on Carbon Emissions in the Yangtze River Delta

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Abstract: A low-carbon economy is the most important requirement to realize high-quality integrated development of the Yangtze River Delta. Utilizing the following models: a super-efficiency slacks-based measure model, a spatio-temporal correlation model, a bivariate LISA model, a spatial econometric model, and a geographically weighted random forest model, this study measured urban industrial eco-efficiency (IEE) and then analyzed its influencing effects on carbon emission in the Yangtze River Delta from 2000 to 2017. The influencing factors included spatio-temporal correlation intensity, spatio-temporal association type, direct and indirect impacts, and local importance impacts. Findings showed that: (1) The temporal correlation intensity between IEE and scale efficiency (SE) and carbon emissions exhibited an inverted V-shaped variation trend, while the temporal correlation intensity between pure technical efficiency (PTE) and carbon emissions exhibited a W-shaped fluctuation trend. The negative spatial correlation between IEE and carbon emissions was mainly distributed in the developed cities of the delta, while the positive correlation was mainly distributed in central Anhui Province and Yancheng and Taizhou cities. The spatial correlation between PTE and carbon emissions exhibited a spatial pattern of being higher in the central part of the delta and lower in the northern and southern parts. The negative spatial correlation between SE and carbon emissions was mainly clustered in Zhejiang Province and scattered in Jiangsu and Anhui provinces, with the cities with positive correlations being concentrated around two locations: the junction of Anhui and Jiangsu provinces, and within central Jiangsu Province. (2) The direct and indirect effects of IEE on carbon emissions were significantly negative, indicating that IEE contributed to reducing carbon emissions. The direct impact of PTE on carbon emissions was also significantly negative, while its indirect effect was insignificant. Both the direct and indirect effects of SE on carbon emissions were significantly negative. (3) It was found that the positive effect of IEE was more likely to alleviate the increase in carbon emissions in northern Anhui City. Further, PTE was more conducive to reducing the increase in carbon emissions in northwestern Anhui City, southern Zhejiang City, and in other cities including Changzhou and Wuxi. Finally, it was found that SE played a relatively important role in reducing the increase in carbon emissions only in four cities: Changzhou, Suqian, Lu'an, and Wenzhou.

Keywords: industrial eco-efficiency; carbon emissions; spatio-temporal correlation; spatial econometric model; Yangtze River Delta

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1. Introduction

The rapid economic development of China, which has been characterized by indus trialization-based urbanization, consumes large amounts of fossil energy, making China the main global CO_2 emitter [1–3]; thus, the country suffers severe pressure from the international community to reduce carbon emissions. Since China's rapid industrialization is still developing, its high proportion of secondary industries, characterized by high pollution, high emissions, and high energy consumption, contributes the majority of carbon emissions [4,5]. Meanwhile, China's traditional industrial structure has been identified as the main reason for the overall increase in carbon emissions [6]. In the context of Chinese efforts to construct an ecological civilization and China's green commitment to building a cleaner and more beautiful world, green, circular, and low-carbon development measures have become inherently important strategies to promote high-quality and sustainable development. These are considered effective, practical measures to achieve peak carbon emission goals by 2030 and carbon neutrality by 2060. As such, the continuous adjustment, optimization, and transformation of industrial structure should be oriented towards green, ecological, and environment-friendly approaches to reduce industrial pollutant emissions and improve industrial eco-efficiency (IEE) [7,8]. This provides an adequate rationale for considering the impacts of IEE.

As the region with the fastest growing and most developed urbanization and industry in China, heavy industry and related economic structures predominate in some areas of the Yangtze River Delta, resulting in a continuous increase in energy consumption and large scale carbon emissions. With the aim of improving green and high-quality integrated development of the Yangtze River Delta, the gradual decoupling of carbon emissions from economic growth has become an important issue. Hence, this study analyzed the spatio-temporal correlation characteristics between carbon emissions and IEE, as well as the effects of IEE on carbon emissions, for cities located in the Yangtze River Delta.

The paper is structured as follows: In Section 2, the literature related to the subject of our research is introduced. Section 3 introduces the methods and data sources, including the multidimensional evaluation index of IEE and the spatial econometric methods used in analyzing the effect of IEE on carbon emissions. Section 4 presents the results, including panel gray correlation characteristics, spatio-temporal association patterns, spatial effects, and local importance analysis of the effect of IEE. Finally, Section 5 provides the conclusions and recommendations of the study.

2. Literature Review

General eco-efficiency is defined as the effectiveness of producing maximum economic outputs together with minimizing natural resource and environmental degradation [9,10]. Due to the flexibility and generality of the concept, eco-efficiency has become a popular quantitative indicator of sustainable development and has been widely applied to various areas of environmental and ecological impact assessment, such as products [11,12], sectors [13,14], and industries [15–17]. Following the core idea of eco-efficiency [18–20], IEE has the dual goals of industrial economic growth and industrial carbon emissions reduction, effectively uniting the material exchange and energy conversion of industrial ecosystems. Further, IEE also couples the subsystems of industrial economy, energy consumption, and environment impact, and accommodates industrial development and resource and environmental protection [21–23]. For these reasons, IEE has become an effective indicator to measure the green and ecological levels of industrial development and has been used as a representative index to evaluate the coordination between industrial development and protection of the environment. Therefore, improving IEE may be a more feasible approach for reduction in carbon emissions compared with other carbon reduction tactics.

The measurement methods associated with eco-efficiency have gradually developed from a single ratio model into complex simulation models, including the ecological footprint model, life cycle accounting, stochastic frontier analysis, the environmentally sustainable value model, and the environmentally extended input-output model [13,24–26]. Notably, due to its advantages of requiring neither a specific functional form nor explicit weights to aggregate the indicators [10,27], the nonparametric data envelopment analysis (DEA) technique has become the most commonly used method to handle the multiple inputs and outputs of efficiency measurement, both flexibly and effectively [28]. To better adapt to the complexity and multi-dimensionality of regional ecosystems, the original DEA model has been further improved to produce the super-efficiency slacks-based measure (Super-SBM) model, which deals with the undesirable outputs and indistinguishable efficiency ranks of decision-making units (DMUs) [29,30]. By incorporating undesirable outputs, the Super-SBM model is more applicable to evaluating IEE that considers not only the environmental performance of industrial production, but also embodies industrial productivity under environmental constraints [19,24,31,32].

Existing studies have theoretically and empirically analyzed the impacts of multiple socio-economic factors including economic growth [33,34], foreign direct investment [35,36], and trade [37,38], as well as policy factors, including policies on local environmental expenditures [39], environmental regulation [40,41], and carbon tax [42], etc. Other targets of analysis have included population factors such as size [43,44] and density [45,46], as well as urbanization [47,48], and technical factors, such as research and development investment [5,49], and green technology innovation [50–52] applied to carbon performance in China. Meanwhile, in terms of the effects of industry, several factors have been identified, such as the rise in the proportion of secondary industries, significantly promoting carbon intensity [53], industrial agglomeration contributing to reducing industrial carbon intensity through economy of scale, and technology spillover [54], and the upgrading and optimization of industrial structure to promote energy conservation and carbon reduction [55–57]. It has also been shown that industrial green transformation and adjustment has significantly reduced carbon intensity [58]. This wide basis of research provides multi-mechanistic and multi-dimensional indicator selection criteria with which to analyze the influencing factors of carbon intensity. Based on the STIRPAT (stochastic impacts by regression on population, affluence, and technology) model and the availability of data, six control variables were selected to detect the direction and degree of their impact on carbon emissions, as described below.

There is a bidirectional relationship between economic growth and carbon emissions. Carbon emissions are considered to be the consequence of production processes and economic activity [3], in that increase (or decrease) of economic growth will lead to increase (or decrease) in carbon emissions. However, the magnitude of the effect of economic growth on carbon emissions may be differentiated at different levels of the economy. In addition, the negative externalities generated by carbon emissions will lower economic growth performance [59]. Therefore, per capita gross domestic product (PGDP) was selected as an indicator to characterize economic development level.

Considering another aspect of the economy, the local fiscal expenditure on environmental protection, education, science, and technology can play a role in improving environmental quality, enhancing residents' awareness of environmental protection, and promoting the progress of energy-saving technology, thereby reducing carbon emissions. However, it can be anticipated that differences in social and economic conditions in different regions will impair the carbon emissions reduction effect of fiscal expenditure across the regions [39]. Therefore, the proportion of local fiscal expenditure in GDP was selected as an indicator to reflect the impact of fiscal expenditure on carbon emissions (denoted as FIN).

In terms of foreign economic factors, the impact of foreign investment on regional environmental conditions can be generally divided into two categories. The first is based on the "pollution heaven" hypothesis, which holds that developed countries transfer heavy polluting industries and high carbon industries to developing countries under a low environmental regulation threshold [3]. The second is the proposed "pollution halo" hypothesis, which holds that when foreign-funded enterprises in developed countries move to host countries, they also bring with them greener and cleaner production technologies that improve local production and environmental protection levels, thus helping to reduce carbon emissions [3]. Therefore, the amount of completed foreign direct investment in each city (FDI) was used as an indicator to represent the status of foreign direct investment, while the average annual price of the renminbi (RMB) exchange rate over a period of years was converted to RMB as a unit, and the GDP index was adjusted to offset the effect of price changes.

It is known that as urbanization accelerates, many economic activities tend to aggregate, while the construction of large-scale infrastructure emerges and energy consumption increases, which improves urban carbon intensity. Meanwhile, urbanization brings economies of scale and for guiding green energy consumption and building ecological towns, urbanization effectively contributes to carbon emissions reduction [60,61]. Therefore, urbanization (URB) was selected as an important indicator and was derived using the proportion of urban population to permanent population.

In terms of the effect of environmental regulation on carbon emissions, there are two opposite views. On the one hand, the government promotes the effect of "forced emission reduction" through a series of command-and-control environmental regulations, which shuts down enterprises with high pollution and high energy consumption or forces them to reduce production scale or to use low-carbon technology. Forced emission reduction is also enacted through a series of market-motivated environmental regulations, which encourage enterprises to use environmental protection technologies and raises energy costs of enterprises by imposing emission taxes, environmental protection taxes, pollution treatment subsidies, etc., thus reducing energy consumption intensity and carbon emissions to a certain extent [62,63]. On the other hand, according to the "green paradox" theory, proposed by Sinn [64], measures aiming to reduce carbon emissions that tax fossil fuel consumption to develop renewable energy have been found to reduce global demand for fossil fuels and undermine the wealth maximization of resource owners. When it is anticipated that such measures could hurt the future price of their resources, resource owners accelerate the extraction of their resources, which results in higher rates of fossil fuel extraction in the short term and increases carbon emissions in the short term. Therefore, this study used the ratio of total environmental governance investment to regional GDP to characterize environmental regulation (denoted as ENV).

In terms of technology, technological progress has positive and negative effects on carbon emissions through the development of production and emission reduction technologies. Production technology progress improves the productivity of factors and energy efficiency, while emission reduction technology progress promotes the reduction in emission intensity [65,66]. However, due to the energy rebound effect and the effects of an extensive economic growth mode, technological progress has been found to stimulate economic activity and increase energy consumption, in turn offsetting energy savings achieved by improved efficiency [67–69]. Therefore, the number of patent applications granted was selected to characterize technological progress (denoted as PAT).

As the first law of geography states that everything is related to everything else, and near things are more related than distant things [70], it can be said that spatial relationships are highly consequential in socio-economic and resource environment analyses [71,72]. It has been confirmed that spatial dependence effects exist in terms of considering regional eco-efficiency [73] and carbon emissions performance [74]. Accordingly, spatial autocorrelation phenomena can be judged by using exploratory spatial data analysis, while specific causal relationships can be explained using the spatial econometric model [75,76]. Given the obvious core-periphery characteristics of its socio-economic development, the socio-economic phenomena of the Yangtze River Delta urban agglomeration show not only temporal correlation but also spatial correlation to some extent. Hence, it is reasonable to use the bivariate LISA [77,78] to reveal the spatial heterogeneous relationships between local carbon emissions and nearby IEE, as well as to use the spatial econometric model to estimate the effects of IEE on carbon emissions.

In summary, it can be stated that many related aspects in the measurement of carbon emissions, the factors influencing carbon emissions, and the connotation and measurement of IEE have been studied. However, deficiencies in our understanding of the topics remain. First, although related studies have analyzed multiple effects of industry on carbon emissions, almost no attention has been paid to the impacts of IEE, which not only integrates green processes and environmental protections but also embodies the synthesis effect of industrial scale and technological progress. As such, it is unknown whether the improvement in IEE and its decomposition terms promote or impede carbon emissions. Second, few studies have explored the spatio-temporal association effects between IEE and carbon emissions among different cities, such as the spatial spillover effect of IEE on carbon emissions from adjacent cities, or the spatio-temporal heterogeneity effect of IEE on carbon emissions among different cities. These questions deserve close attention, since the answers are not only important for helping China to reduce carbon emissions, but also for providing a reference for industrializing regions.

3. Materials and Methods

3.1. Super-SBM Model

The Super-SBM model has the advantages of avoiding radial and oriented deviation, incorporating undesirable outputs into the efficiency evaluation model, and discriminating between the efficient DMUs equal to 1 [79–82]. Hence, the Super-SBM model, with undesirable outputs, better represents the nature of regional IEE evaluation.

Now we consider the industrial production process with n DUMs which uses m input factors to produce s1 desirable outputs and s2 undesirable outputs. The three vectors are respectively expressed as: $x \in R^m$, $y^d \in R^{s_1}$, $y^u \in R^{s_2}$ among which x, y^d, and y^{ud} represents the inputs, desirable outputs, and undesirable outputs. The matrices of $Y^d > 0$, $Y^{ud} > 0$ are defined as $X = [x_1, \cdots, x_n] \in R^{m \times n}$, $Y^d = [y_1^d, \cdots, y_n^d] \in R^{s_1 \times n}$, and $Y^{ud} = [y_1^u, \cdots, y_n^u] \in R^{s_2 \times n}$. Assume that the DMUk $\left(x_k, y_k^d, y_k^{ud}\right)$ is slacks-based-measure-efficient. Then, the Super-SBM with undesirable outputs can be defined as:

$$\beta_{SE} = \min \frac{1 + \frac{1}{m}\sum\limits_{i=1}^{m} \frac{s_i^-}{x_{ik}}}{1 - \frac{1}{s_1+s_2}\left(\sum\limits_{r=1}^{s_1} \frac{s_r^d}{y_{rk}^d} + \sum\limits_{t=1}^{s_2} \frac{s_t^{ud}}{y_{tk}^{ud}}\right)}$$

$$\begin{aligned}
& s.t.\ x_i^k \geq \sum_{j=1, j\neq k}^{n} x_{ij}\lambda_j - s_i^- \\
& y_{rk}^d \leq \sum_{j=1, j\neq k}^{n} y_{rj}^d \lambda_j + y_r^d \\
& y_{tk}^{ud} \geq \sum_{j=1, j\neq k}^{n} y_{tj}^{ud} \lambda_j + y_t^{ud} \\
& 1 - \frac{1}{s_1+s_2}\left(\sum_{r=1}^{s_1} \frac{y_r^d}{y_{rk}^d} + \sum_{t=1}^{s_2} \frac{y_t^{ud}}{y_{tk}^{ud}}\right) > 0 \\
& \lambda,\ s^-,\ s^+ \geq 0 \\
& i = 1,\ 2, \cdots m;\ \ j = 1,\ 2, \cdots n(j \neq k);\ \ r = 1,\ 2, \cdots s_1;\ \ t = 1,\ 2, \cdots s_2
\end{aligned} \tag{1}$$

where β_{SE} is the objective function whose value can be more than 1, λ_j is a weighting factor, the subscript k means a DMU whose efficiency is being estimated, and the vectors s^-, s^d, and s^{ud} denote the slacks of inputs, desirable outputs, and undesirable outputs, respectively.

The above Super-SBM model is based on the assumption of constant returns-to-scale, thus by adding the restrictions $\sum_{j=1,\neq k}^{n} w_j = 1$, it can convert a variable return to scale. Further, the overall IEE factor can be decomposed into pure technical efficiency (PTE) and scale efficiency (SE) [83]. The factor PTE refers to the efficiency of resource allocation, utilization, pollution control, management, and production technology. The factor SE refers to the efficiency of the scale of resources, in terms of measuring whether the DMUs are the optimal production scale [84]. Using MaxDEA Ultra software, the IEE, PTE, and SE of 41 cities in the Yangtze River Delta urban agglomeration from 2000 to 2017 were obtained.

3.2. Panel Gray Correlation Model

The gray correlation model is a mature and effective tool to deal with uncertainty systems that have only "partial information known" and which are influenced by multiple factors [85,86]. However, being restricted by either the single object dimension or time dimension, the traditional model cannot overcome the defects of inconsistent gray relational order caused by the change of object ranking in the panel data. To better consider the differences of object and time dimensions of the panel data, Dang et al. [87] put forward the panel gray correlation model, which introduces incremental differences to investigate the development characteristics of different indicators in each period from the time dimension. The new model also utilizes deviation differences to measure the distribution characteristics of different indicators in each object from the object dimension and extracts the relative differences of development degrees and the direction of different indicators in both object and time dimensions in order to judge the extent of positive and negative correlation. Due to the complexity of the derivation process needed to calculate the incidence coefficient, the specific formula expression is omitted from this paper and can be referred to in Dang et al. [87].

3.3. Bivariate LISA Model

The bivariate *LISA* statistic is defined as [72,78]:

$$B_{LISA} = N\sum_{i=1}^{N}\sum_{j\neq i}^{N} w_{ij} z_i^{\mathrm{ce}} z_j^{iee} / \sum_{i=1}^{N}\sum_{j\neq i}^{N} w_{ij} \tag{2}$$

where N is the total number of cities; w_{ij} is spatial weight matrix based on queen contiguity; z_j^{ce} is the z-score standardization of carbon emissions in city i; and z_j^{iee} is the z-score standardization of industrial eco-efficiency in city j. The heterogeneous clusters from the local bivariate *LISA* can be divided into four types, namely, $\mathrm{H_iH_j}$, $\mathrm{L_iL_j}$, $\mathrm{L_iH_j}$, and $\mathrm{H_iL_j}$. If the city is identified as $\mathrm{High_{carbon\ emission}}$-$\mathrm{High_{Iee}}$, it means that its carbon emissions are significantly higher than the average value of all cities, and the industrial eco-efficiency of adjacent cities is significantly higher than the average value of all cities. This means that the city has a higher level of carbon emissions and is surrounded by cities with higher industrial eco-efficiency.

3.4. Spatial Econometric Model

The general form of the spatial econometric model is known as the spatial Durbin model (SDM), which is hereafter used in the text, and can be defined as follows [72,75]:

$$y_{it} = \lambda\sum_{j=1}^{n} w_{ij}y_{jt} + \beta X_{jt} + \sum_{j=1}^{n} w_{ij}X_{ijt}\gamma + c_i + a_t + \varepsilon_{it}, \qquad \varepsilon_{it} \sim i.i.d(0,\delta^2) \tag{3}$$

where y_{it} is the carbon emission for city i at year t; n is the total number of cities; $w_{ij}y_{jt}$ is the spatial lag of carbon emission; X_{it} is the independent variables; β is the corresponding coefficients for X_{it}; λ is the spatial spillover of adjacent regional carbon emission; is the corresponding spatial lag coefficient of the adjacent regional independent variables; is an independently and identically distributed error term for i and t with zero mean and a variance of σ^2; and c_i and α_t denote the spatial and temporal effects, respectively. Before the model is estimated, the hypotheses H_0: $\gamma = 0$ and H_0: $\gamma + \lambda\beta = 0$ should be performed to test whether SDM can be simplified to the spatial lag model (SLM) and the spatial error model (SEM), respectively. These tests can adopt the form of a Wald or LR test.

For estimating the outcome of the SDM, note that the estimated coefficient of the explanatory variables has no significance; however, the direct and indirect effects of the explanatory variables should be fully understood as follows: The direct effect refers to the influence of the change of independent variables in adjacent regions on the local area, while the indirect effect refers to the influence of the change of independent variables in a certain region on its neighboring areas [74].

3.5. Data Sources

Different from the conventional econometric model, which uses remote sensing light to estimate carbon emissions, Chen et al. [88] adopted variant coefficient models and the normalized difference index to estimate the carbon emissions of 334 prefecture-level cities in China from 1992 to 2017. Their method was based on more accurate and easier-to-understand techniques of inter-calibration of the DMSP/OLS (Defense Meteorological Program Operational Line-Scan System) and NPP/VIIRS (National Polar-orbiting Partnership Visible Infrared Imaging Radiometer Suite) datasets, and was found to be effective for describing long-term, full-coverage CO_2 data at the scale of prefecture-level cities.

In this study, based on a related IEE evaluation system and data availability, four indicators were selected to characterize industrial land, labor, electricity, and water consumption. Industrial added value was selected as the expected output indicator, while industrial waste-water discharge, exhaust emissions, and smoke and dust emissions were the undesirable output indicators. The evaluation system components for input-output and variable description are listed in Table 1.

Table 1. The evaluation indicators of industrial eco-efficiency (IEE).

Primary Indices	Secondary Indices	Unit	Max	Min	Mean	Stdev
Input indicators	Industrial land area	Ten thousand tons	736.8	1.5	50.61	91.82
	Industrial employee	Ten thousand people	629	11.4	112.83	91.29
	Industrial electricity	kW·h	1202.04	1.63	128.83	168.12
	Industrial water consumption	Ten thousand tons	320,400	978	25,567.98	47,975.59
Expected output indicator	Industrial added value	Ten thousand yuan	7606.45	15.1	826.89	1030.34
Undesirable output indicator	Industrial waste water discharge	Ten thousand tons	85,735	548.9	12,930.35	15,649.08
	Industrial exhaust emissions	Ten thousand tons	17,041	14	1880.61	2483.51
	Industrial smoke and dust emissions	Ten thousand tons	3159	3.4	525.26	573.73

All datasets used in determining the indicators of IEE and related independent variables were obtained from the Jiangu Statistical Yearbook (2001–2018), Anhui Statistical Yearbook (2001–2018), Zhejiang Statistical Yearbook (2001–2018), China Statistical Yearbook for Regional Economy (2001–2014), the Statistical Bulletins of National Economic and Social Development for each city, and the statistical websites of certain provinces and cities compiled by the government during 2001–2018. According to the administrative division in 2020, the data of Chaohu City before 2011 were incorporated into Hefei, Ma'anshan, and Wuhu cities. The final determined number of cities for this study was 41. In order to account for inflation, relevant economic data such as the industrial added value, GDP, and financial expenditure were converted based on the year 2000.

4. Results

4.1. Panel Gray Correlation between IEE, PTE, SE, and Carbon Emissions

Before calculating the correlation coefficients between IEE, PTE, SE, and carbon emissions, the logarithmic operator was used to preprocess indicators of each city, then both the spatial and temporal correlation coefficients were obtained, and are visualized in Figures 1 and 2, respectively. As can be seen from Figure 1, the temporal correlation intensity between IEE and carbon emissions exhibited an inverted V-shaped fluctuation trend, and the correlation coefficient increased continuously from 0.008 in 2000 to 0.190 in 2008, then continuously dropped, reaching 0.026 in 2017, with an annual average value of 0.043. This implies that IEE exerted first an enhanced, and then weakened, positive impact on carbon emissions, but that the impact was relatively low. The temporal correlation intensity between PTE and carbon emissions was generally below zero with an annual average value of −0.051 and exhibited a W-shaped fluctuation trend. This illustrates that the improvement of PTE could effectively promote the reduction in carbon emissions. The temporal correlation coefficient between SE and carbon emissions was generally similar to the trend between IEE and carbon emissions and exhibited an inverted V-shaped fluctuation trend with an annual average value of 0.088, implying that the improvement in IEE was dependent on SE; meanwhile, SE was positively correlated with increase in carbon emissions.

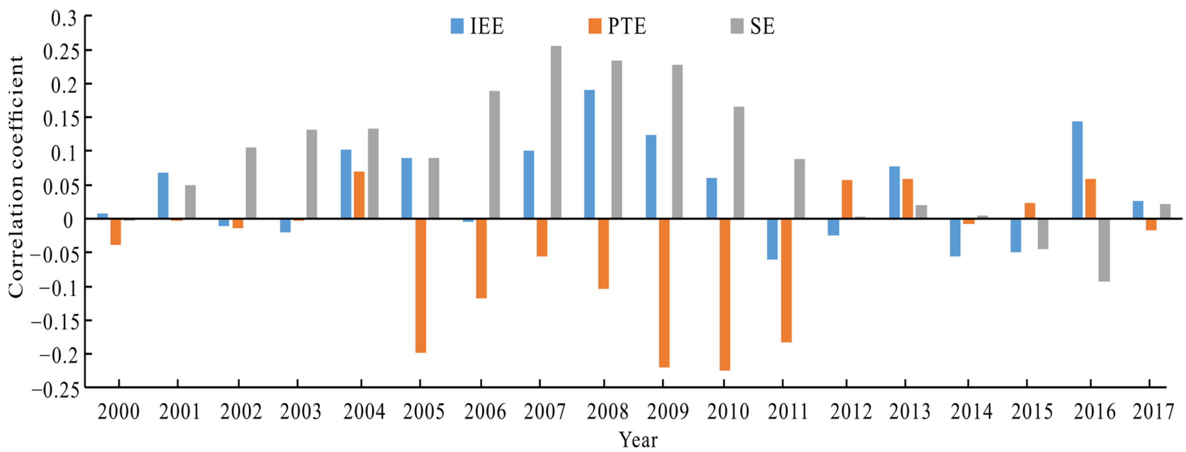

Figure 1. Temporal correlation intensity between IEE, PTE, SE, and carbon emissions.

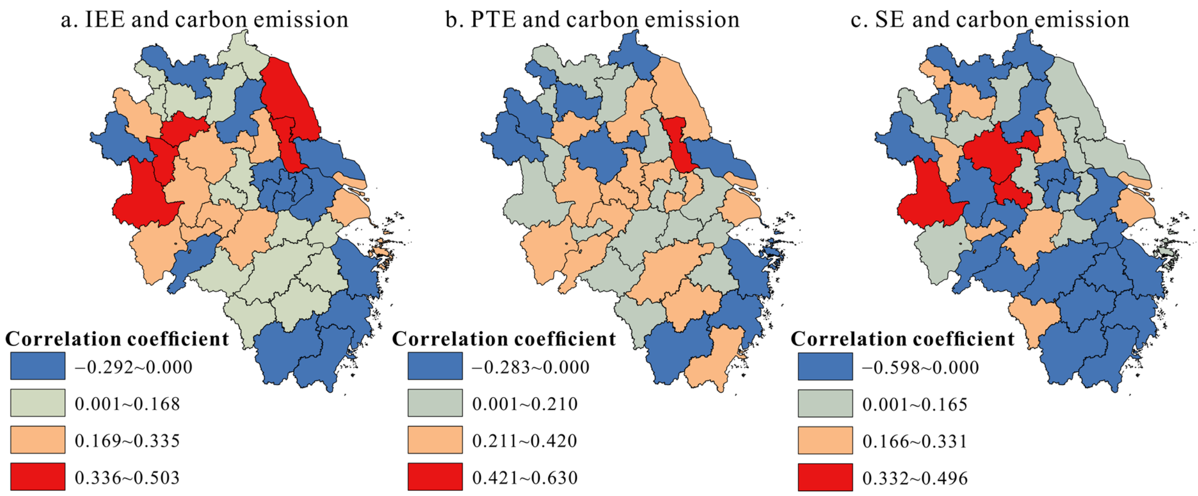

Figure 2. Spatial correlation intensity between (**a**) IEE and carbon emissions, (**b**) PTE and carbon emissions, (**c**) SE and carbon emissions.

The spatial correlation coefficient was divided into four intervals: below 0, and three equal intervals from 0 to the maximum value of 0.503, 0.630, and 0.496, respectively. It can be seen from Figure 2 that the average spatial correlation intensity between IEE and carbon emissions was 0.104. The negative correlation cities accounted for 31.71% and were mainly clustered in southern Zhejiang Province and southern Jiangsu Province. These are developed cities that followed green industrial production and paid more attention to ecological environmental protection, which contributed to reducing carbon emissions. While the positive correlation cities accounted for 68.29%, with the high correlation intensity cities mainly being distributed in central Anhui Province, and Yancheng and Taizhou cities. In order to speed up industrial development, these cities developed large numbers of labor intensive and polluting low-end industries, which brought environmental damage and increased carbon emissions. The average spatial correlation intensity between PTE and carbon emissions was 0.132, and the spatial pattern was higher in the central part of the delta and lower in the northern and southern parts. The negative correlation cities accounted for 24.39%, while the positive correlation cities accounted for 68.29%, implying that most of the urban industrial enterprises were lagging behind in the research, development, and use of green production and pollution control technologies, resulting in an increase in carbon emissions. The average spatial correlation intensity between SE and carbon emissions was −0.024. The negative correlation cities accounted for 48.78% and were mainly clustered in Zhejiang Province and scattered in Jiangsu and Anhui provinces. The positive correlation cities accounted for 51.22% and were mainly concentrated at the junction of Anhui and Jiangsu provinces and within central Jiangsu Province, implying that the improvement of SE effectively promoted carbon emissions reduction.

4.2. Spatio-Temporal Association Pattern between IEE and Carbon Emissions

Although the panel gray correlation revealed the spatio-temporal correlation between IEE and carbon emissions, it ignored the underlying spatio-temporal association type between IEE and carbon emissions. Hence, the bivariate LISA spatio-temporal clustering was used to identify the association type, in order to investigate their local features more clearly, both significant and non-significant association types in 2000, 2008, and 2017 were visualized, as shown in Figure 3.

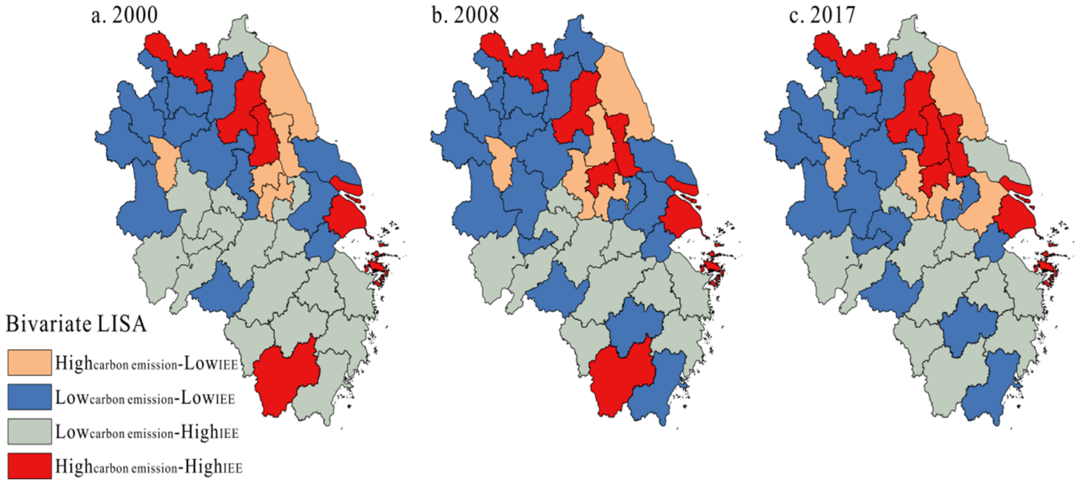

Figure 3. Local spatial association between IEE and carbon emissions in (**a**) 2000, (**b**) 2008 and (**c**) 2017.

In 2000, the $L_{\text{carbon emission}}L_{\text{IEE}}$ type was mainly clustered in the northern cities of Anhui, and scattered in Nanjing, Suzhou, Suqian, Nantong and Jiaxing city, which had less industry-intensive economies with long-term economic development being characterized by low energy consumption and low emissions. In 2008, the spatial scope of $L_{\text{carbon emission}}L_{\text{IEE}}$-type cities further expanded with Wuxi, Lianyungang, Wenzhou, Jinhua, Hefei, and Tongling city joining the $L_{\text{carbon emission}}L_{\text{IEE}}$ type. In 2017, the spatial pattern of $L_{\text{carbon emission}}L_{\text{IEE}}$-type cities was almost identical to that of 2008, with some minor adjustments. For instance, Lianyungang, Suzhou, Nantong, and Huaibei city retreated from the $L_{\text{carbon emission}}L_{\text{IEE}}$ type, and Wuhu city became an $L_{\text{carbon emission}}L_{\text{IEE}}$ type.

In 2000, there were six cities belonging to the $H_{\text{carbon emission}}H_{\text{IEE}}$ type, including Shanghai, Xuzhou, Huai'an, Zhoushan, Yangzhou, and Lishui city, with the high carbon emissions surrounded by high IEE cities, which was due to rapid urbanization and economic growth that promoted carbon emissions. In 2009, except for removal of Yangzhou from the $H_{\text{carbon emission}}H_{\text{IEE}}$ type, other cites remained as $H_{\text{carbon emission}}H_{\text{IEE}}$ type, and Zhenjiang and Taizhou became the $H_{\text{carbon emission}}H_{\text{IEE}}$ type. In 2017, the spatial pattern of the $H_{carbon\ emission}H_{IEE}$ type was generally similar to that of 2008, but Lishui exited from the $H_{carbon\ emission}H_{IEE}$ type, and Yangzhou once again became the $H_{carbon\ emission}H_{IEE}$ type.

The number of cities belonging to the $H_{carbon\ emission}L_{IEE}$ type was relatively small, and mainly centered around the $H_{carbon\ emission}H_{IEE}$ type, with Changzhou, Yancheng, and Huainan remaining as the $H_{carbon\ emission}L_{IEE}$ type in 2000, 2008, and 2017.

In 2000, the $L_{carbon\ emission}H_{IEE}$ type cities were mainly distributed in Zhejiang and Southern Anhui, which benefited from the improvement in low-carbon transportation and infrastructure construction, the implementation of low-carbon life, and the promotion and development of forest carbon sequestration, thus, effectively improving the low-carbon production living ecological space. In 2008, the $L_{carbon\ emission}H_{IEE}$ type cities tended to contract to the northern Zhejiang and southern Anhui areas. In 2017, the spatial pattern of $L_{carbon\ emission}H_{IEE}$ type cities was generally similar to that of 2008, with Lianyungang, Nantong, Huaibei, and Lishui city evolving into the $L_{carbon\ emission}H_{IEE}$ type.

4.3. The Spatial Effect of IEE, PTE, and SE on Carbon Emissions

Using Stata15.0 software, first, the pooled ordinary least squares (OLS) regression was estimated to diagnose the spatial autocorrelation of OLS residuals. The Moran's I test of OLS residue was 5.377, significant at the 1% statistic level, illustrating a strong spatial effect in the OLS residue. Second, the Lagrange Multiplier (LM) and Robust LM tests were used to evaluate whether the SLM model or the SEM model was more applicable than the non-spatial effect model. The test results are shown in Table 2. The LM (lag), LM (error), and the Robust LM (error) tests were significant at the 1% level, and the Robust LM (lag) was significant at the 10% level. In comparison, the value of the LM (error) and Robust LM (error) tests were higher than those of LM (lag) and Robust LM (lag) tests, implying that the SEM model was more suitable for capturing the spatial effects of the model. Since both the SLM and SEM models are non-nested spatial models, Wald and likelihood ratio (LR) tests were then needed to test whether the SDM model could be simplified to the SLM or SEM model. The statistical results determined that the SDM model could be used instead of either the SLM or SEM models. Moreover, the Hausman test showed that the fixed effect should be considered. Hence, the SDM model including the fixed effect was selected to explain the impact of IEE and its decompression terms on carbon emissions.

Table 2. Test results of spatial model.

Test	Statistics	Test	Statistics
LM (lag) test	71.181 ***	LR test spatial lag	93.89 ***
Robust LM (lag) test	2.978 *	LR test spatial error	133.23 ***
LM (error) test	549.296 ***	Wald test spatial lag	68.92 ***
Robust LM (error) test	481.094 ***	Wald test spatial error	92.87 ***
Hausman test	−115.18		

Note: *** Significant at the 0.01 level; ** Significant at the 0.05 level; * Significant at the 0.1 level.

The estimated results of the impacts of IEE, PTE, and SE on carbon emissions were obtained (Table 3). The results showed that the spatial autocorrelation coefficients of carbon emissions were significantly positive at the 1% significance level, implying that the increase in carbon emissions in neighboring cities exerted a positive spatial spillover effect on local carbon emissions, further revealing the importance of joint control for regional carbon emissions.

Table 3. Regression results of spatial Durbin models.

	SDM-IEE	SDM-PTE	SDM-SE
IEE	−0.035 (−2.64) ***		
PTE		−0.036 (−1.83) *	
SE			−0.033 (−1.89) *
PGDP	0.159 (6.90) ***	0.154 (6.70) ***	0.148 (6.62) ***
FIN	0.079 (7.69) ***	0.081 (7.86) ***	0.081 (7.83) ***
FDI	−0.003 (−0.60)	−0.004 (−0.80)	−0.004 (−0.72)
URB	0.064 (1.59)	0.067 (1.67) *	0.065 (1.62)
PAT	0.025 (3.57) ***	0.025 (3.59) ***	0.027 (3.95) ***
ENV	−0.008 (−1.35)	−0.008 (−1.40)	−0.008 (−1.44)
W×IEE	−0.021 (−0.87)		
W×PTE		0.001 (0.03)	
W×SE			−0.042 (−1.29)
W×PGDP	−0.112 (−3.48) ***	−0.112 (−3.46) ***	−0.111 (−3.53) ***
W×FIN	0.012 (0.83)	0.013 (0.90)	0.011 (0.78)
W×FDI	−0.004 (−0.45)	−0.006 (−0.68)	−0.005 (−0.61)
W×URB	−0.236 (−5.34) ***	−0.235 (−5.35) ***	−0.243(−5.48) ***
W×PAT	−0.015 (−1.71) *	−0.017 (−1.85) *	−0.013 (−1.38)
W×ENV	0.023 (1.76) *	0.022 (1.69) *	0.022 (1.70) *
rho	0.671 (24.48) ***	0.677 (25.26) ***	0.667 (23.99) ***
R^2	0.958	0.957	0.958
$Sigma^2$	0.004	0.004	0.004
Log likelihood	936.483	933.938	934.999

Note: *** Significant at the 0.01 level; ** Significant at the 0.05 level; * Significant at the 0.1 level.

For the SDM model, the estimated coefficients of explanatory variables could not directly reflect their marginal effect; moreover, it was difficult to accurately measure the direct influence of independent variables on the dependent variable. Therefore, a partial differential equation was used to calculate the direct effects, indirect effects, and total effects of each independent variable, as shown in Table 4.

Table 4. Direct, indirect, and total effects of spatial Durbin models.

	Direct Effect			Indirect Effect			Total Effect		
	SDM-IEE	SDM-PTE	SDM-SE	SDM-IEE	SDM-PTE	SDM-SE	SDM-IEE	SDM-PTE	SDM-SE
IEE	−0.046 (−2.90) ***			−0.126 (−1.95) *			−0.171 (−2.32) **		
PTE		−0.041 (−1.78) *			−0.069 (−0.61)			−0.110 (−0.88)	
SE			−0.048 (−2.27) **			−0.178 (−2.07) **			−0.226 (−2.27) **
PGDP	0.157 (7.00) ***	0.151 (6.72) ***	0.145 (6.69) ***	−0.009 (−0.12)	−0.016 (−0.22)	−0.029 (−0.41)	0.148 (1.92) *	0.135 (1.68) *	0.116 (1.55)
FIN	0.097 (9.78) ***	0.099 (10.04) ***	0.098 (9.93) ***	0.182 (6.19) ***	0.193 (6.61) ***	0.18 (6.14) ***	0.278 (8.67) ***	0.292 (9.14) ***	0.278 (8.70) ***
FDI	−0.005 (−0.90)	−0.006 (−1.22)	−0.006 (−1.11)	−0.018 (−0.78)	−0.026 (−1.11)	−0.023 (−1.00)	−0.023 (−0.88)	−0.032 (−1.24)	−0.028 (−1.12)
URB	0.017 (0.47)	0.02 (0.55)	0.018 (0.48)	−0.539 (−7.67) ***	−0.541 (−7.57) ***	−0.55 (−7.9) ***	−0.522 (−7.23) ***	−0.521 (−7.05) ***	−0.533 (−7.46) ***
PAT	0.025 (3.61) ***	0.025 (3.50) ***	0.029 (4.19) ***	0.001 (0.03)	−0.004 (−0.18)	0.013 (0.67)	0.025 (1.21)	0.021 (0.91)	0.042 (1.95) *
ENV	−0.003 (−0.41)	−0.004 (−0.47)	−0.004 (−0.52)	0.052 (1.30)	0.049 (1.21)	0.048 (1.22)	0.049 (1.06)	0.046 (0.98)	0.044 (0.97)

Note: *** Significant at the 0.01 level; ** Significant at the 0.05 level; * Significant at the 0.1 level.

According to Table 4, the direct effect of IEE on carbon emissions was significantly negative at the 1% level, implying that the improvement of IEE contributed to reducing local carbon emissions. The indirect effect of IEE on carbon emissions of neighboring cities was significantly negative at the 10% level, indicating that the improvement in local IEE emerged as the determinant for the reduction in local carbon emissions, and brought a reduction in carbon emissions in surrounding cities. The overall effect of IEE was significantly negative at the 5% level, indicating that improvement in IEE could reduce carbon emissions. This is because the Yangtze River Delta region has striven to accelerate the upgrade of the industrial economic growth mode and has made significant efforts to phase out industrial enterprises with higher energy consumption and which create serious environmental pollution. Moreover, the region has also actively implemented ecological environmental governance policies and measures to improve the ecological environment. Considering this, in the context of regional collaborative governance, this study shows that the impact of IEE on carbon emissions exhibited a marked local effect and a regional spillover effect.

The direct impact of PTE on carbon emissions was significantly negative at the 1% level, implying that the improvement of PTE contributed to reducing local carbon emissions. In terms of the indirect effects and total effect, PTE did not play a significant role in reducing the carbon emissions of adjacent cities, implying that the effect of PTE was confined to the local city. This was probably because the improvement in PTE was influenced by management, institutions, and technology absorption capacity. Accordingly, if the function, scale, and development concept of industrial structure in the surrounding cities were greatly different from the local cities, the requirements for low-carbon technology application and innovation would not be met. Moreover, there existed a certain gap between the current PTE and the optimal technological frontier, which jointly restricted the positive spillover effect of PTE.

Both the direct effect and indirect effect of SE on carbon emissions were significantly negative at the 5% level, indicating that the improvement in SE would not only alleviate local carbon emissions, but also reduce carbon emissions in the surrounding cities through the spatial spillover effect. The overall effect of SE was significantly negative, implying the optimal SE and the positive environmental externality of industrial agglomeration formed by the optimal configuration of industrial production factors were conducive to mitigating carbon emissions.

With respect to the impact of control variables on carbon emissions, the significance and sign of each of the control variables was generally similar under the regression models of SDM-IEE, SDM-PTE, and SDM-SE. Specifically, the direct effect of PGDP was significantly positive, but its indirect effect was negative and insignificant, illustrating that economic development likely increased local carbon emissions but had little impact on adjacent cities. This is probably because the high carbon-producing features of the economy and energy structure were very prominent in the delta region. Although the economic growth of the Yangtze River Delta region had entered the middle and late stages of rapid industrialization development, secondary industry still dominated the economic structure over the long term, resulting in rapid growth demand for coal, oil, natural gas, and other fossil energy.

In terms of financial considerations, the increase in FIN not only exerted a significantly positive impact on local carbon emissions, but also significantly increased carbon emissions in adjacent cities. On the one hand, this was because, local governments assumed the responsibility for financial expenditure for economic development, education, medical care, social security, and environmental protection with limited tax resources. Under the premise of limited financial resources, governments competed to attract more opportunities to increase fiscal revenues. However, environmental protection investment was usually large-scale and slow to take effect, and furthermore, was not used as a performance evaluation indicator in this study. Hence, local governments were more inclined to lowering the threshold of environmental protection and shifting to expenditure for capital construction. On the other hand, environmental pollution had a positive externality, in that, in the case of local governments lacking cooperation, each government would take on free-riding to reduce its own environmental protection investment and reduce its responsibility for protecting the environment, thereby aggravating the local and adjacent cities' carbon emissions.

The direct and indirect impact of FDI on carbon emissions was negative, but not significant, indicating that the "pollution refuge effect" was not validated in the Yangtze River Delta region. Instead, the inflow of FDI through the pollution halo effect and the scale effect brought an advanced production technology and management mode, which exerted a restraining effect on carbon emissions. However, the promotion effect of foreign investment on economic growth stimulated all cities to lower local thresholds of environmental regulation to attract foreign investment, thereby introducing pollution-intensive industries, which aggravated energy consumption and carbon emissions. Hence, the negative environmental effect offset the positive environmental effect of FDI, resulting in an insignificant impact of FDI.

The direct impact of URB on carbon emissions was positive, but not significant. This was owing to energy consumption being the most important driving force of urbanization. With the improvements of urbanization, increasingly more energy and resources were consumed, which inevitably increased carbon emissions. Yet, with the construction of resource-saving and environment-friendly urban societies, the urbanization of the delta region gradually evolved into a new type, characterized by green production, green living and consumption patterns, and green economic transformation. This counteracted the positive carbon effects of urbanization, resulting in an insignificant impact. Meanwhile, the indirect effect of URB on carbon emissions was significantly negative. This was because the urban economy development required large amounts of funding and infrastructure construction. However, due to urban competition, the more resources a city gathered, the less resources its surrounding cities possessed. This effect, therefore, inhibited the development of urbanization in neighboring regions and thus contributed to reducing carbon emissions.

The direct impact of PAT on carbon emissions was significantly positive, while the indirect impact of PAT on carbon emissions was insignificant. These effects were because the related technological progress was not biased towards energy conservation or emissions reduction, but rather toward product innovation and productivity improvement. This promoted the expansion of enterprise-scale progress and led to an increase in carbon emissions intensity. In addition, the introduction and application of low-carbon technology increased short-term enterprise production costs, which was not conducive to enterprises participating in market competition.

The direct effect of ENV on carbon emissions was negative, but not significant, while the indirect impact of ENV on carbon emissions was positive and insignificant. These effects were because there remained prominent contradictions between regional economic development, environmental governance, and energy consumption in the short term. Although effective environmental regulation could force enterprises to invest in measures to reduce carbon emissions, such as pollution control, production process improvement, and environmental technology innovation, the inhibition emission effect was ultimately offset by the green paradox effect. That paradox effect was created from the expansion of reproduction to compensate for the increased cost arising from short-term environmental regulations [64], which was thereby not conducive to long-term low-carbon development.

4.4. Analysis of the Local Importance of IEE, PTE, and SE on Carbon Emissions

The SDM model revealed the overall impacts of IEE, PTE, and SE, but without considering their local effects. Therefore, to further explore the importance of IEE, PTE, and SE at the local scale, the geographically weighted random forest regression (GRF) [89] was applied to determine the local importance effects of IEE, PTE, and SE to the increase in carbon emissions. The values were expressed in the form of percentage increase in mean square error (%IncMSE); the higher the value of %IncMSE, the greater the importance of a given variable. It can be seen from Figure 4 that the importance of IEE, PTE, and SE varied dramatically in space. The positive effect of IEE had obvious spatial heterogeneity on the increase in carbon emissions, in that its importance increased from the east to west. Compared with other cities in Jiangsu and Zhejiang provinces, the improvement of IEE was more likely to alleviate the increase in carbon emissions in cities clustered in northern Anhui Province. Generally, the importance of PTE exhibited a similar spatial pattern compared with IEE, in that cities with a higher importance effect were mainly clustered in northwestern Anhui Province, in south Zhejiang Province, and were scattered in a few cities, such as Changzhou and Wuxi. While SE was not a relatively important factor affecting the increase in carbon emissions, its importance distribution was more dispersed in space, with relatively high importance in Changzhou, Suqian, Lu'an, and Wenzhou cities.

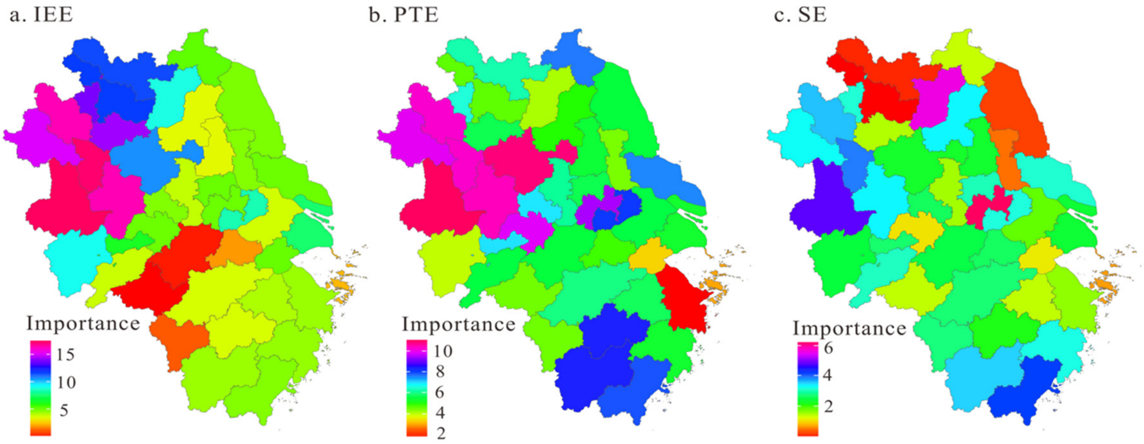

Figure 4. Spatial distribution of the importance of (**a**) IEE, (**b**) PTE and (**c**) SE.

5. Conclusions and Recommendations

The spatial-temporal evolution and formation mechanisms of IEE and carbon emissions have been extensively discussed, and the impact of industrial production on carbon emissions has been investigated from single dimensions of industrial production indicators. However, the relationship between IEE and carbon emissions has not received the attention it deserves, and the exact link between IEE and carbon emissions has not been systematically examined. Hence, we used the Super-SBM model to measure IEE and its decomposition terms for 41 cities in the Yangtze River Delta from 2000 to 2017. Based on these measurements, the impacts of IEE and its decomposition terms on carbon emissions were further analyzed from spatio-temporal correlation and heterogeneous perspectives. The main conclusions are as follows:

(1) The temporal correlation intensity between IEE and SE and carbon emissions exhibited an inverted V-shaped variation trend, while the temporal correlation intensity between PTE and carbon emissions exhibited a W-shaped fluctuation trend. In space, the negative correlation between IEE and carbon emissions was mainly distributed in the developed cities of the Yangtze River Delta, while the positive correlation cities were mainly distributed in central Anhui Province, and Yancheng and Taizhou cities. The spatial correlation intensity between PTE and carbon emissions exhibited a spatial pattern of being higher in the central part of the delta and lower in the northern and southern parts. The negative spatial correlation between SE and carbon emissions was mainly clustered in Zhejiang Province and scattered in Jiangsu and Anhui provinces, with the positive correlation cities being concentrated along the junction of Anhui and Jiangsu provinces and within central Jiangsu Province.

(2) The direct and indirect effects of IEE on carbon emissions were significantly negative, implying that the improvement in IEE contributed to reducing carbon emissions. The direct impact of PTE on carbon emissions was significantly negative, while its indirect effect was insignificant. Both the direct and indirect effects of SE on carbon emissions were significantly negative.

(3) The importance impacts of IEE, PTE, and SE on carbon emissions increase exhibited significant spatial heterogeneity. The positive effect of IEE was more likely to alleviate the increase in carbon emissions in northern Anhui City. In terms of technology, PTE was more conducive to reducing the increase in carbon emissions in northwestern Anhui City, southern Zhejiang City, and other cities including Changzhou and Wuxi. Finally, it was found that SE played a relatively important role in reducing the increase in carbon emissions in only four cities, Changzhou, Suqian, Lu'an, and Wenzhou.

This study on the impact of IEE on carbon emissions provides importance guidance for planning the construction of ecological civilizations and high-quality integrated development in the Yangtze River Delta. In order to further apply the potential of IEE in promoting carbon emission reduction, relevant policy suggestions have been proposed as follows.

First, ecological industry should be the fundamental direction of industrial development in the future. Cities in the Yangtze River Delta should continue to speed up green industrial transformation and upgrading, making full use of the current technological levels to give full scope to advantageous industries, but also strengthening the ability of green technological innovation and renewal, to improve IEE and realize the unification of the industrial economy and ecological construction. Moreover, it is necessary to continuously improve technical management levels and production scale efficiency, as well as to speed up the progress of technical efficiency. Such efforts would aid in coordinating the development of industrial management levels, technology applications, and scale expansion.

Second, cities in the Yangtze River Delta should promote the co-governance of carbon emissions due to the spatial spillover effect of carbon emissions identified in this study. Efforts should be made to establish a "five-synergy" operating mechanism featuring "coordinated case-handling, prevention, construction, improvement, and restoration," thus creating a social ecological environment pattern of multiple co-governance and sharing. Such efforts would prevent and control carbon emissions at the source to reduce emissions increases. Moreover, in order to exert the positive spillover effects of IEE, PTE, and SE on carbon emissions reduction, cities should strengthen the collaborative research and development of green production technology and emissions reduction technology. To this end, cities should also strengthen the exchange of advanced organization and management modes between industrial enterprises.

Third, to achieve the decoupling of carbon emissions from economic growth, low-carbon circular economies should be vigorously developed to prevent economic growth being sacrificed. To this end, the government should promote resource-conserving and environmentally friendly urbanization, as well as raise public awareness of low-carbon living and green consumption, while at the same time formulating a long-term regulation mechanism to reduce carbon emissions considering local conditions. Moreover, local governments and enterprises should increase their investment in green science and technology innovation, as well as increase the introduction of low-carbon equipment and enhance regional cooperation. In addition, when introducing foreign investment, local governments should raise the environmental access threshold and refuse to bring in low-efficiency, high-consumption, or high-polluting foreign enterprises. Moreover, foreign direct investment should be guided into energy conservation and environmental protection and fully facilitate the pollution halo effect.

We acknowledge that there are some limitations to this study. First, academics have not reached a consensus on the evaluation system of IEE, and due to the influence of the availability of data, the measurement of IEE does not fully consider social policies and other closely related factors. Second, although it has been confirmed that improvement in IEE contributes to reducing carbon emissions, its underlying influencing mechanisms require further consideration, that is, whether IEE can indirectly affect carbon emissions through other intermediate variables, which can be assessed with the help of a mediation model. Third, we need to further explore the heterogeneous influence of IEE on the carbon emissions of cities of different sizes and the differential influence of IEE on carbon emissions in different periods.

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