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RESEARCH ARTICLE

Industrial environmental efficiency and its influencing factors in China: analysis based on the Super-SBM model and spatial panel data

Yanhua Chen[1] · Bin Zhu[1] · Xiangxiang Sun[1] · Guanghui Xu[2]

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Abstract

The industry sector is not only an important driving force for economic growth but also the largest sector of resource consumption and pollution emission. In this study, we first constructed a super-slack-based measure (Super-SBM) model including the resource consumption and undesirable outputs, and estimated the industrial environmental efficiency (IEE) in China from 2007 to 2016. Afterwards, based on the spatial autocorrelation test and the spatial Durbin model, the spatio-temporal evolution and the influencing factors of IEE were analyzed. The empirical results are obtained as follows: the average IEE from 2007 to 2016 was 0.5176. IEE in the east of China was the highest, whereas it was the lowest in the west. The spatial autocorrelation test showed that the regions with similar levels of IEE in China had significant spatial agglomeration, whereas the local spatial distribution of IEE was unbalanced. The high-high IEE agglomeration areas were located in Liaoning, Jilin, and Inner Mongolia. The low-low IEE agglomeration areas were concentrated in Gansu, Ningxia, and Sichuan. Finally, according to the spatial Durbin panel model and spillover effect decomposition, GDP, FDI, human capital, environmental governance investment, research and development investment, and urbanization have a positive impact on IEE. The industrial and energy consumption structures have a negative impact on IEE. Therefore, the central government should focus on balancing IEE of different provinces and regions, increasing investment in industrial pollution treatment, and encouraging FDI to improve IEE.

Keywords China's industrial environmental efficiency · Spatio-temporal evolution · Super-SBM model · Spatial Durbin model

Introduction

Better coordination of the relationship between economic development, environmental protection, and resource conservation has become the most important challenge faced by humans (Yu et al. 2019; Shen et al. 2020). Sustainable development is a realistic choice to balance economic development and pollution emissions. As a pillar of the national economy, the industry sector plays a core role in promoting economic development. However, the industry sector is also the largest in terms of resource consumption and pollution emissions (Wang et al. 2016; Zhu et al. 2019). In 2017, China's industry occupied 40.1% of GDP but emitted 71.7% of dust, 66.6% of SO_2, and 83% of CO_2. Moreover, emissions of waste gas, wastewater, and solid waste increased by 206%, 17%, and 116%, respectively, from 2006 to 2015. In contrast, the growth rate of urban industrial output was only 39%. Industrial development has brought about serious environmental consequences and ecological damage (National Bureau of Statistics of China (NBSC) 2016). The exhaustion of resources and deterioration of the ecological environment caused by industrial development have substantially hindered the sustainable development of the green economy (Li et al. 2018; Zhu et al. 2019).

Faced with the dual pressures of energy consumption and environmental sustainability, the Chinese government has taken many measures to improve energy and environmental efficiency. For instance, the government has actively formulated policies, such as the 13th Five-Year Ecological Environmental Protection Plan, and implemented the Paris Agreement. Furthermore, China has pledged to reduce CO_2

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✉ Bin Zhu
zhubincer@fzu.edu.cn

[1] School of Economics and Management, Fuzhou University, Fuzhou 350116, China

[2] Department of Economic Management, Guangxi Financial Vocational College, Nanning 530007, China

emissions by 60–65% in 2030 compared with 2005. However, China has a vast territory and uneven economic development, which will inevitably lead to differences in the spatial distribution of industrial environmental efficiency (IEE) in the process of sustainable development (Zhang et al. 2015). Consequently, to achieve high-quality industrial development in China, it is imperative to understand the changes in IEE and its influencing factors.

In fact, achieving high-level ecological efficiency is a common concern around the world. The process of economic growth is inevitably accompanied by energy consumption, especially in transition economies. In developed or developing countries, a low IEE constitutes a significant barrier to environmental sustainability. With the largest industrial economy and energy consumption in the world (Zhang et al. 2017), the China's IEE characteristics and influencing factors are a vital epitome for other developing countries.

We attempted to use the super-slack-based measure (Super-SBM) model to estimate IEE and its influencing factors in 30 Chinese provinces. This study provides the following contributions. First, we employed the Super-SBM model to analyze the characteristics and spatio-temporal evolution of IEE. Unlike most previous studies on IEE that used the traditional radial data envelopment analysis (DEA) model as a primary measurement tool, this study reflected the undesirable output efficiency. Moreover, the Super-SBM model could reveal more accurately the changing characteristics of IEE in China. Second, we investigated the spatial correlation and distribution pattern of IEE and clarified the spatial dependence and heterogeneous characteristics of IEE in China. Third, we employed a spatial econometric model to identify the influencing factors of IEE in China. Traditional econometric models, such as Tobit and multiple linear regression, tend to be applied to test the influencing factors of IEE, whereas spatial econometric models are rarely used (Li et al. 2018). Therefore, our research framework provided a more accurate evaluation of the spatially differentiated characteristics of IEE, and it can be used as a reference tool for improving IEE.

The rest of the paper is organized as follows: "Literature review" presents the literature review; "Method and data" elaborates on the Super-SBM and spatial economic models; "Variable selection and data source" introduces some selected variables and data sources; and "Spatio-temporal evolution characteristics of industrial environmental efficiency" analyzes the spatio-temporal evolutionary characteristics and influencing factors of IEE. Finally, we discuss the empirical results and illustrate the policy implications.

Literature review

IEE refers to the impact of economic value created by industrial systems on the environment, aiming to analyze the coordination between industrial development and the environment (Sun et al. 2020). This section reviews the existing studies on IEE from the following three aspects: the ecological efficiency model, measurement of IEE, and influencing factors of IEE.

Research on ecological efficiency model

DEA is the main method used to evaluate ecological efficiency in the recent empirical literature (Song et al. 2014; Yu et al. 2019). Chen and Yeh (1998) and Wang et al. (2012) estimated energy efficiency based on the DEA model. Nevertheless, the DEA model cannot deal with slack variables. Tone (2001) presented a new DEA method which is called slacks-based measure (SBM) to evaluate the efficiency. SBM is a non-radial method that directly deals with slack variables and eliminates radial deviations (Song et al. 2013). Based on the SBM model, Tone (2002) also proposed a Super-SBM model to evaluate efficiency more accurately and reliably. This model integrated the advantages of the SBM model and super-efficiency model and evaluated the decision-making units (DMUs) more precisely and reliably (Li and Shi 2014; Chen et al. 2019). Zhang et al. (2017) measured the low-carbon economy efficiency of 30 provinces in mainland China using the Super-SBM method. The study found that China's regional economy has not achieved a low-carbon growth but improved at a rate of 4.5% per year. Gokgoz and Erkul (2019) estimated the energy efficiency of European countries based on the Super-SBM method. The Super-SBM model has also been successfully applied to estimate the efficiency of banking, hotels, and transport (Chiu et al. 2011; Avkiran and Cai 2014).

Research on industrial environmental efficiency measurement

China's IEE has attracted widespread attention. Wu et al. (2014) applied a new fixed sum undesirable output DEA model to measure IEE in China, revealing that economic development is directly related to environmental performance. Zhang et al. (2015) and Lu and Yuan (2017) evaluated IEE in China by utilizing the super-efficiency DEA model and VRS-DEA model. At the same time, many scholars focused on the impacts of undesirable emissions (e.g., SO_2 and CO_2) on IEE in China. Li and Shi (2014) and Wang et al. (2016) calculated the energy efficiency with undesirable outputs based on a slack non-radial DEA model. Yu et al. (2019) proposed an optimized matrix-type NDEA model. Li and Shi (2014) first adopted the Super-SBM model to evaluate China's industrial energy efficiency at the sectoral level. Guo et al. (2019) evaluated IEE in western China using the SBM models from a regional perspective, whereas Xie et al. (2019) measured IEE in China based on the multivariate DEA models with undesirable outputs at the industry level.

In addition, scholars have studied the spatio-temporal evolution characteristics of IEE by using traditional quantitative statistical models, such as the convergence coefficient and the Malmquist index. For instance, Zhang et al. (2015) utilized the coefficient of variation to analyze the spatial convergence of environmental efficiency in China. They revealed that the spatial disparity of IEE among regions gradually diminished. Guo et al. (2019) employed the Malmquist index to estimate the change in IEE in western China. Wen et al. (2016) analyzed the spatial dependence of IEE in mainland China using the spatial autocorrelation model.

Research on influencing factors of industrial environmental efficiency

Many studies have focused on the factors influencing ecological efficiency based on regression models. Zhong and Hu (2016) explored the influence of natural resource endowment on China's ecological efficiency by using econometric models and found that the improvement in human capital was conducive to promoting urban ecological efficiency. Moutinho et al. (2017) utilized the quantile regression technique to examine the factors that affected 26 European countries, and pointed out that these European countries had great differences in environmental efficiency, whereas environmental taxes positively affected less eco-efficient countries. Dogan and Turkekul (2016) and Dogan et al. (2019) explored the validity of the environmental Kuznets curve (EKC) hypothesis and found that fossil fuels, energy consumption, and urbanization were the most common causes of anthropogenic pressure in Mexico, Indonesia, Nigeria, and Turkey. They also proposed to formulate effective energy policies so that CO_2 emissions could be reduced in the USA. Regarding the ecological efficiency effects of FDI, Blomström and Kokko (1998) and Javorcik and Wei (2004) applied the multivariate regression analysis method to form two conflicting views of FDI, promoting and inhibiting ecological efficiency. For China's industrial sector, Wang et al. (2016) applied a truncated regression model and found that coal consumption was the major factor affecting environmental efficiency. Li et al. (2018) used a spatio-temporal dual-fixed spatial error model and discovered that economic development, technological progress, foreign investment, and industrial agglomeration were positively correlated with IEE, whereas the industrial structure and government regulation were negatively correlated.

To sum up, scholars have conducted extensive studies on IEE in China and obtained significant research results. DEA has been widely applied in the field of ecological efficiency (Guo et al. 2019). As a newly developed DEA model, the Super-SBM model has apparent advantages in evaluating DMU of undesirable outputs (Li and Shi 2014; Chen et al. 2019), but its application at the provincial level of IEE in China is still negligible. Moreover, most of the existing studies have assumed spatial independence between the regions, and there is a lack of discussion on spatial correlation. Therefore, it is impossible to reflect IEE from the perspective of time and space. Finally, spatial econometric models have seldom been employed to analyze the influencing factors, which need to be further explored.

This study utilizes the Super-SBM model to evaluate IEE in 30 Chinese provinces from 2007 to 2016. It also analyzes the spatio-temporal characteristics of IEE and its evolution process. Then, a spatial autocorrelation model is employed to explore the spatial relationship and correlation of IEE in China. Lastly, the spatial econometric model of influencing factors affecting IEE is constructed, and spatially divergent features are tested, with the purpose of providing theoretical support for promoting IEE.

Method and data

Measurement of industrial environmental efficiency

This study utilized IEE to examine the sustainable performance of green industrial development in different regions. The traditional DEA method fails to address the problem of non-radial relaxation and undesirable output (Banker et al. 1984). As such, according to Gómez-Calvet et al. (2014), we employed the Super-SBM model, taking undesirable outputs into account to assess IEE. We assumed a system with L DMUs. Each DMU makes use of m input factors and produces s_1 desirable outputs and s_2 undesirable outputs. Three vectors were defined: $x \in R^m$, $y^g \in R^{s_1}$, and $y^b \in R^{s_2}$. The matrices X, Y^g, and Y^b were determined as follows:

$$X = [x_1, x_2, \cdots, x_L] \in R^{m \times L} \tag{1}$$

$$Y^g = \left[y_1^g, y_2^g, \cdots, y_L^g\right] \in R^{s_1 \times L} \tag{2}$$

$$Y^b = \left[y_1^b, y_2^b, \cdots, y_L^b\right] \in R^{s_2 \times L} \tag{3}$$

According to Tone (2001), the SBM model with undesirable outputs is expressed as:

$$\begin{gathered}
\beta = \min \frac{1 - \frac{1}{m} \sum_{i=1}^{m} \frac{S_i^-}{x_{i0}}}{1 + \frac{1}{S_1 + S_2}\left(\sum_{r=1}^{s_1} \frac{S_r^g}{y_{r0}^g} + \sum_{t=1}^{S_2} \frac{S_t^b}{y_{t0}^b}\right)} \\
s.t.\ x_0 = X\lambda + s^- \\
y_0^g = Y^g\lambda - s^g \\
y_0^b = Y^b\lambda + s^b \\
s^- \geq 0, s^g \geq 0, s^b \geq 0, l \leq e\lambda \leq u, \lambda \geq 0
\end{gathered} \tag{4}$$

where λ represents the weight vector; and the vectors $s^- \in R_+^m$, $s^g \in R_+^{s_1}$, and $s^b \in R_+^{s_2}$ indicate the slacks of the inputs, desirable outputs, and undesirable outputs, respectively. The objective function β takes a value within [0, 1]. If $\beta = 1$, $s^- = s^b = s^g = 0$, the evaluated DMU is considered effective.

Based on Charnes and Cooper (1962), the above formulas were transformed into equivalent linear programming problems:

$$\beta^* = \min \frac{1 + \frac{1}{m}\sum_{i=1}^{m} \frac{S_i^-}{x_{ik}}}{1 - \frac{1}{S_1+S_2}\left(\sum_{r=1}^{S_1} \frac{y_r^g}{y_{rk}^r} + \sum_{t=1}^{S_2} \frac{y_t^b}{y_{tk}^b}\right)}$$
$$s.t.\quad x_i^k \geq \sum_{j=1, j\neq k}^{n} x_{ij}\lambda_j - S_i^- \tag{5}$$
$$y_{rk}^g \leq \sum_{j=1, j\neq k}^{n} y_{rj}^g \lambda_j + y_r^g$$
$$y_{tk}^b \leq \sum_{j=1, j\neq k}^{n} y_{tj}^b \lambda_j + y_t^b$$
$$1 - \frac{1}{S_1+S_2}\left(\sum_{r=1}^{S_1} \frac{y_r^g}{y_{rk}^g} + \sum_{t=1}^{S_2} \frac{y_t^b}{y_{tk}^b}\right) > 0$$
$$\lambda, s^-, s^+ \geq 0$$
$$i = 1, 2, \cdots, m; j = 1, 2, \cdots, n(j\neq k); r = 1, 2, \cdots, s_1; t = 1, 2, \cdots, s_2$$

where β^* is IEE evaluated by the undesirable output-based SBM method. Other variables have the same meaning as in Eq. (4).

Spatial econometric model

Spatial autocorrelation model

We focused on the application of spatial correlation of IEE to different regions. Contrary to the traditional Malmquist index calculation method and bootstrap regression model, the spatial autocorrelation model is an important method of regional spatial issues research and can effectively combine data and graphs to comprehensively demonstrate the differences and similarities of spatial distribution. The spatial autocorrelation model was used to analyze the spatial correlation of IEE. We adopted two spatial autocorrelation indices: (1) Moran's *I*, the global spatial autocorrelation index, which examines the spatial correlation of IEE in the whole country; and (2) Local Moran's *I*, the local spatial autocorrelation index, which is used to examine the spatial correlation of a region and its adjacent regions. The spatial autocorrelation index was calculated as follows:

$$Moran's\ I = \frac{\sum_{i=1}^{n}\sum_{j\neq i}^{n} W_{ij}\left(Y_i - \overline{Y}\right)\left(Y_j - \overline{Y}\right)}{S^2 \sum_{i=1}^{n}\sum_{j\neq i}^{n} W_{ij}}, i\neq j \tag{6}$$

$$Local\ Moran's\ I_i = Z_i \sum_{j=1}^{n} w_{ij} Z_{ij} \tag{7}$$

where Y_i and Y_j represent the values of IEE in regions *i* and *j*, respectively; *n* represents the total number of regions; $S^2 = \frac{1}{n}\sum_{i=1}^{n}\left(Y_i - \overline{Y}\right)^2$ and $\overline{Y} = \frac{1}{n}\sum_{i=1}^{n} Y_{ij}$ W_{ij} represent the spatial weight matrix; Z_i and Z_j denote the standardization of the IEE value in regions *i* and *j*, respectively; and W_{ij} is the spatial weight. The absolute value of Moran's *I* indicates the degree of spatial correlation: the greater the spatial correlation, the higher the absolute value of Moran's *I*.

The local Moran's *I* index is used for the identification of the local spatial autocorrelation of IEE. The spatial units can be divided into four types. The high-high type and low-low type indicate that both the area in question and its adjacent areas have a high degree and low degree of IEE aggregation, respectively. The low-high type and high-low type indicate that the investigated area has a low degree and high degree of IEE aggregation, whereas the adjacent regions have a high degree and low degree of IEE aggregation, respectively.

Spatial panel model

This study also used a spatial panel model, predominantly including the spatial lag model (SLM), spatial error model (SEM), and spatial Durbin model (SDM). SDM adds the space-lag term of the explanatory variables based on SLM and SEM.

SLM mostly explores whether the independent variables in an area are affected by the independent variables in adjacent areas. The model's equation is as follows:

$$Y = \alpha + \rho WY + \beta X + \varepsilon \tag{8}$$

where *Y* and *X* represent the dependent and independent variables, respectively; *W* is the spatial weight matrix; ρ is the spatial lag autoregressive coefficient; β is the estimated coefficient of the independent variable; and ε is a random perturbation term.

SDM reveals if the dependent variable of a region is affected by the dependent variable and independent variables of the adjacent region. The model uses the following equation:

$$Y = \alpha + \rho WY + \beta X + \theta WX + \varepsilon \tag{9}$$

where θ represents the coefficient of the space-lag term of the independent variable, and other values are the same as in Eq. (8).

Variable selection and data source

Evaluation index system

The Super-SBM model was employed to evaluate IEE in the research framework, which considers the economic outputs and environmental performance. To make an accurate estimate of IEE, we selected the input-output indicators from basic economic and environmental indicators. Output indicators consisted of desirable and undesirable outputs. According to Yang and Li et al. (2019) and Li et al. (2019), we selected labor, capital, energy consumption, and water consumption as input indicators. Industrial value added was determined as a desirable output indicator, whereas sulfur dioxide emissions, wastewater emissions, and waste gas emissions were adopted as undesirable output indicators (see Table 1).

Influencing factors of spatial econometric models

Many factors influence IEE. Existing studies show that economic development, industrial structure, FDI, energy intensity, science and technological input, human capital, urbanization, and environmental taxation are the main factors influencing IEE. Economic development, industrial structure, FDI, energy consumption structure, research and development (R&D) investment, human capital, urbanization, and environmental governance investment were selected as explanatory variables to analyze the dynamic changes in IEE (Yu et al. 2013) (see Table 2). It is worth noting that R&D investment and human capital play an important and beneficial role in the enhancement of ecological efficiency (Fang and Chang 2016; Alam et al. 2019; Sun et al. 2020). Thus, the "per capita average years of education" and "ratio of R&D investment to GDP" were used as proxies for human capital and R&D investment, respectively. In addition, fossil fuel energy consumption is the foremost reason for the increase in total CO_2 emissions (Moutinho et al. 2018; Dogan and Inglesi-Lotz 2020). Moreover, coal, as the main fossil fuel, has been occupying a large proportion of China's energy consumption structure for a long time (Cheng et al. 2019). In 2018, coal consumption of China's industrial sector reached 3.65 billion tons, accounting for 81.4% of the country's total coal consumption and 96.8% of all of the material production sectors (National Bureau of Statistics of China (NBSC) 2019), which directly affected the improvement in IEE. As a result, we characterized the energy consumption structure using the ratio of coal consumption to energy consumption.

Data sources

The data in this study were obtained from the China Statistical Yearbook, China Macroeconomic Database, China Compendium of Statistics (1949–2008), China Environmental Statistics Yearbook, China Environmental Yearbook, China Population and Employment Statistics Yearbook, China Labor Statistics Yearbook, China Energy Statistics Yearbook, the Ministry of Commerce Statistical database, and the National Bureau of Statistics. Considering the availability of the data, it covered 30 provinces in China. The study period was chosen from 2007 to 2016. This study used the 0–1 adjacency matrix to measure the spatial weight matrix, that is, if two regions are adjacent, the value equals 1, and if they are not adjacent, the value is 0. With Hainan Province being far from the mainland, we defined Hainan as adjacent to Guangdong Province.

Spatio-temporal evolution characteristics of industrial environmental efficiency

Time series characteristics of industrial environmental efficiency

We discuss the temporal evolution characteristics and regional differences in IEE in China. Figure 1 shows the trend of average IEE between 2007 and 2016. As shown in Fig. 1, the average IEE from 2007 to 2016 was 0.5176. The average IEE increased from 0.3769 in 2007 to 0.5746 in 2016. The most substantial increase in IEE happened between 2007 and 2008, mainly due to the implementation of a series of measures from 2005 to 2007 when the Chinese government accelerated the treatment of industrial pollution sources, developed a circular economy, and encouraged enterprises to introduce advanced environmental technology to upgrade traditional techniques. Li et al. (2018) proposed the following scheme for the value of IEE: if IEE is below 0.5, it is considered a low IEE; if the value of IEE is between 0.500 and 0.699, it is a medium IEE; if the value of IEE ranges between 0.700 and 0.799, it is considered a medium-high IEE; and if

Table 1 Input-output indicators

	Category	Specific indicators
Input indicators	Labor input	Total number of urban employees
	Capital input	Fixed asset investment
	Resource inputs	Total energy consumption
		Total water consumption
Output indicators	Desirable output	Industrial value added
	Undesirable outputs	Sulfur dioxide emissions
		Wastewater emissions
		Waste gas emissions

Table 2 Influencing factors of IEE

Explanatory variable	Abbreviation	Unit	Remarks
Per capita GDP	X1	–	Logarithm of per capita GDP
Industrial structure	X2	%	Ratio of secondary industry value added to GDP
FDI	X3	%	Ratio of foreign direct investment to GDP
Energy consumption structure	X4	%	Ratio of coal consumption to energy consumption
Human capital	X5	Year	Per capita average years of education
Environmental governance investment	X6	%	Ratio of environmental governance investment to GDP
R&D investment	X7	%	Ratio of R&D investment to GDP
Urbanization	X8	%	Ratio of urban population to total population

the IEE value is above 0.8, it is a high IEE. According to our calculation results, the overall IEE is still low in China, although it greatly improved between 2007 and 2016.

To analyze the regional variations of IEE in China, all the samples were divided into three groups[1]. As shown in Fig. 1, there is a significant regional difference in IEE. For example, the average IEE in the eastern area is the highest, whereas the average IEE in the western area is the lowest.

Spatio-temporal patterns of industrial environmental efficiency

We further discuss the spatial pattern and distribution of IEE in space. Based on the estimation of IEE, we selected the time points between 2007 and 2016 to further analyze the spatial evolution of IEE using ArcGIS. Figure 2 shows the spatial variation of IEE. In 2007, the provinces with IEE greater than 0.4 were mainly distributed in Shandong, Liaoning, Fujian, Tianjin, and Inner Mongolia, whereas the provinces with IEE less than 0.169 were mainly concentrated in Guizhou, Jilin, Xinjiang, Sichuan, Gansu, and Shanxi. In 2016, the provinces with high IEE were located in Inner Mongolia, Liaoning, Shandong, and Tianjin, whereas the provinces with a low IEE concentrated in Shanxi, Gansu, and Sichuan. According to the IEE rating mentioned above and our calculation results, the overall IEE in China is still low and is characterized by spatial non-equilibrium. That is to say, IEE of the eastern region is higher than that of the western region. The reasons are as follows: the eastern region has the highest level of economic development, strong scientific and technological capabilities, and the advantages in foreign exchange and advanced technology introduction. The western region has experienced the strategic cultivation of western development and has made significant progress in technology, talent, and IEE management, but its IEE is lower than that in the eastern and central regions. This conclusion was confirmed by Wu et al. (2014) and Zhu et al. (2019).

Spatial autocorrelation analysis of industrial environmental efficiency

In this study, we also tested the spatial correlation of IEE. We used the GeoDa software to evaluate the spatial autocorrelation of IEE. Table 3 presents the global Moran index of IEE from 2007 to 2016. As shown in Table 3, the global Moran indices of IEE are positive at least at the 5% level of significance in each period, indicating a strong spatial autocorrelation in regional IEEs. In other words, IEE in a region is affected by IEEs in the adjacent areas. Regions with similar IEEs present the trend of geographic agglomeration. The global Moran's I index shows a trend of weakening fluctuations as the index dropped from 0.3120 in 2007 to 0.1995 in 2016. The spatial correlation of regional IEEs in China reveals a changing trend. Consequently, regional governments should strengthen cooperation to improve IEE.

To test the spatial correlation and distribution pattern of IEE in space, the Moran Lisa clustering map was used to analyze IEE and visually demonstrate the clustering types in

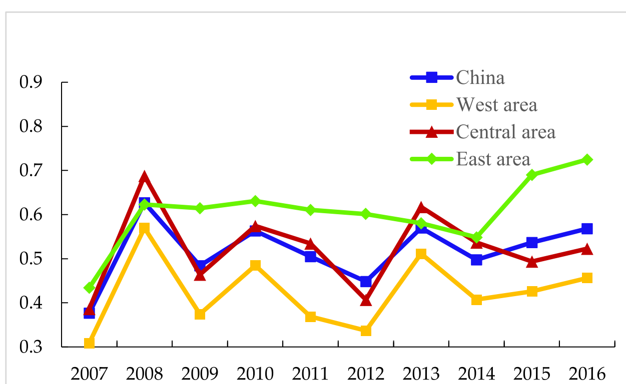
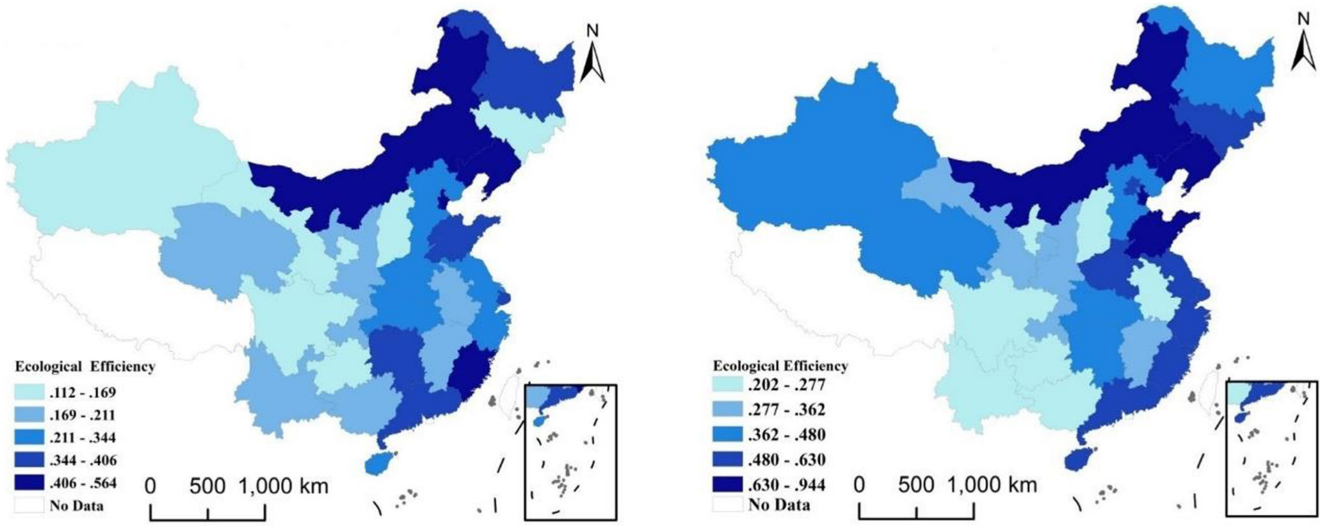


Fig. 1 Trend of average IEE from 2007 to 2016

[1] The east area includes Beijing, Tianjin, Liaoning, Hebei, Shandong, Jiangsu, Shanghai, Zhejiang, Fujian, Guangdong, and Hainan; the central area includes Shanxi, Anhui, Jiangxi, Henan, Hubei, Hunan, Jilin, and Heilongjiang; the west area includes Inner Mongolia, Guangxi, Chongqing, Sichuan, Guizhou, Yunnan, Shaanxi, Ningxia, Gansu, Qinghai, and Xinjiang.



(a)Spatial variation of IEE in 2007 **(b)Spatial variation of IEE in 2016**

Fig. 2 Spatial variation of China's inter-provincial IEE

China. Due to the limited space available, the spatial autocorrelations of IEE for only 2007 and 2016 are discussed below.

The high-high agglomeration indicates that the area with high IEE is adjacent to another area with high IEE, which is characterized by the diffusion. The low-high agglomeration specifies that the area with a low IEE is adjacent to another area with high IEE, which is characterized by the transition. The low-low agglomeration reflects that the area with a low IEE is adjacent to another area with a low IEE. The high-low agglomeration shows that the area with a high IEE is adjacent to the area with a low IEE, showing the polarization characteristics.

The high-high agglomeration was mainly observed in the northeast region: Liaoning, Jilin, and Inner Mongolia in 2016. Technological progress, industrial structure, and geographical location affect IEE positively. Being China's main heavy industry R&D production base, the northeast region concentrates several major industrial projects, such as aerospace and energy, and lays the foundation for China's industrialization. This region is also known as the "cradle of new China's industry" (Zhu et al. 2019). Since 2003, this region has continuously implemented the strategy of revitalizing the northeastern traditional industrial base, transformed the economic development model, developed green industries, and, thus, continuously improved its IEE. Moreover, Liaoning, Jilin, and Inner Mongolia possess abundant natural resources, reasonable industrial bases, and increasingly close regional cooperation mechanisms, all of which have a positive effect on the surrounding region. Therefore, IEE of the northeast region has a positive impact on IEE of adjacent areas, with a significant diffusion effect.

Table 3 Moran index of IEE in China from 2007 to 2016

Year	Moran's I	P value
2007	0.3120	0.014
2008	0.3917	0.008
2009	0.3004	0.007
2010	0.3011	0.011
2011	0.2893	0.004
2012	0.2767	0.008
2013	0.2658	0.004
2014	0.2522	0.001
2015	0.2330	0.001
2016	0.1995	0.007

The low-low agglomeration was mainly distributed in Gansu, Ningxia, and Sichuan, where economic development was relatively low, and policy support was insufficient in 2007. The low-low agglomeration was concentrated in Sichuan, Guizhou, and Yunnan in 2016. These provinces are geographically separated from the hinterland and have a weak economic base and negligible resource acquisition. For instance, in 2007, the energy consumption per unit of industrial added value of Gansu and Ningxia was 4.29 standard coal per RMB 10,000 and 8.12 standard coal per RMB 10,000, respectively, both far above the national average (2.83 tons of standard coal per RMB 10,000). Instead, the comprehensive utilization of industrial solid waste in Gansu was running at only 31.51% of the national average of 35.55 million tons, and that in Ningxia was 18.50%. Apparently, these two provinces were struggling with the lagging IEE. The change in spatial correlation between Guizhou and Yunnan was mainly due to the fact that the two provinces are located in the western region with a relatively underdeveloped economic growth model, and IEE is highly influenced by the degree of implementation of environmental protection policies. Therefore, IEE was low. The low-high agglomeration was prevalent in Jilin and Liaoning. For these areas, technical exchanges and cooperation with neighboring provinces should be strengthened to improve IEE.

Influencing factors of industrial environmental efficiency

The spatial correlation test showed that IEE is characterized by a significant spatial correlation. We further discuss the factors influencing IEE based on the spatial econometric model. The factors impacting IEE include socio-economic factors, industrial structure, FDI, energy consumption structure, R&D investment, human capital, urbanization, and environmental policy. Consequently, the spatial econometric model is used to estimate the influencing factors of IEE and detect the characteristics of spatial differentiation. We selected the following index factors contributing to IEE: per capita GDP, industrial structure, FDI, energy consumption structure, environmental governance investment, R&D investment, human capital, and urbanization. First, we focused attention on the selection of the panel regression model. As shown in Table 4, the LM-lag and LM-error test statistics are significant at the 1% level of significance, which indicates that the non-spatial model should be rejected. The LM test and robust LM test are significant, with a significance level of at least 5%. This indicates that the factors affecting IEE include not only independent variables and their lag terms but also some unobservable error terms.

Table 4 reports on the results of the regression estimates of the influencing factors affecting IEE. According to Table 4, the regression coefficient of per capita GDP is positive at the 1% level of significance, which is consistent with the expected results. This result indicates that GDP has a positive impact on IEE. Pollution emissions from economic development activities will inevitably affect IEE (Tunc and Turuk-Asik 2009). Economically developed areas have evident advantages in energy-saving technology and pollution emission governance (Li et al. 2013). Namely, the more developed a region's economy is, the higher the ecological technology and pollution control level will be, thus promoting the improvement in local IEE. W* X1 also has a positive and significant effect. The direct and indirect effects of GDP are significant at the 1% level.

The regression coefficient of industrial structure is negative at the 1% level of significance, which is consistent with the expected results. The proportion of secondary industry increased by 1%, whereas IEE decreased by 0.0263%. As the secondary industry contains several heavy industrial enterprises, most enterprises adopt extensive development, which results in a serious waste of resources and environmental pollution. Therefore, the increase in the proportion of secondary industry aggravates the deterioration of pollutant emissions and the ecological environment, making the improvement in IEE unfavorable. The indirect effect of industrial structure is significant.

The regression coefficient of FDI is positive at the 1% level of significance. This result indicates that FDI is conducive to the promotion of IEE. Foreign investment has advanced concepts and green management experience, which provide support for strengthening environmental awareness, improving energy saving, and reducing emissions. Meanwhile, an increasing number of regions have begun to attach importance to the quality of foreign investment, actively introducing green foreign investment with high technology, energy-saving practices, and environmental protection. The increase in green foreign investment also leads to an improvement in IEE. Therefore, FDI promotes the improvement in IEE. The indirect effect of FDI is significant.

The regression coefficient of the energy consumption structure is negative, which passes the significant test at the 1% level. We used the ratio of coal consumption to energy consumption to measure the energy consumption structure. Coal mining and coal consumption aggravate pollution emissions, resulting in serious water, soil, and air pollution. Coal consumption is the main source of global warming and greenhouse gas emissions (Wang et al. 2016). The increase in atmospheric pollutants is not conducive to the improvement in IEE. Moreover, in China, the use of coal is predominant in heavy industrial enterprises in the industrial sector, which are generally characterized by sloppy production and high energy consumption, thus additionally impeding the improvement in IEE. W* X4 also has a negative and significant effect. The direct effect of the energy consumption structure is significant.

The regression coefficient of human capital is significantly positive at the 1% level of significance. This result shows that human capital has a positive impact on IEE. Sun et al. (2020) claimed that human capital contributes to the enhancement of ecological efficiency. Li and Shi (2014) insisted that insufficient development of human capital would reduce the efficiency of advanced technology and equipment introduction, generating greater resource waste. In general, human capital improves economic development and technological progress (Fang and Chang 2016). The application and promotion of energy-saving technologies by human capital can lead to higher economic benefits and energy utilization rates. The direct effect of human capital is significant.

The regression coefficient of environmental governance investment is significantly positive. Our study results showed that environmental governance investment has a beneficial impact on IEE. With increasingly consequential environmental pollution, the government has begun to attach more importance to environmental governance. Environmental governance investment provides subsidies for equipment renewal, encourages the adoption of new technologies, and reduces

Table 4 Regression results of influencing factors affecting IEE

Variables	(1) SDM	(2) Direct effects	(3) Indirect effects
GDP (X1)	0.0441***	0.0096***	0.0345***
	(4.02)		
Industrial structure (X2)	− 0.0263***	− 0.0115	0.0378***
	(2.90)		
FDI (X3)	0.0198**	0.0132	0.0066***
	(2.45)		
Energy consumption structure (X4)	− 0.0590***	− 0.0297***	− 0.0293
	(− 3.10)		
Human capital (X5)	0.0675***	0.0421***	0.0254
	(3.76)		
Environmental governance investment (X6)	0.0663***	− 0.0227***	− 0.0436
	(4.19)		
R&D investment (X7)	0.2259***	0.1787***	0.0472***
	(3.82)		
Urbanization (X8)	0.2829***	− 0.0125	0.2954***
	(2.76)		
W* X1	0.0223**		
	(2.20)		
W*X2	− 0.0317		
	(1.01)		
W* X3	0.0054		
	(0.87)		
W* X4	− 0.4889***		
	(3.19)		
W*X5	0.0103		
	(1.23)		
W* X6	0.0455		
	(0.90)		
W* X7	0.0372**		
	(2.55)		
W* X8	0.0191		
	(1.41)		
ρ	0.1789***		
	(3.67)		
LM-lag	16.585***		
Robust LM-lag	15.017***		
LM-error	10.936***		
Robust LM-error	8.564***		
-cons	0.1079		
	(0.56)		
R	0.7762		

*Significance at the 10% level; **significance at the 5% level; *** significance at the 1% level

production costs, thereby promoting IEE. As such, environmental governance investment promotes IEE. The direct effect of environmental governance investment is significant.

The regression coefficient of R&D investment is positive, which also passes the significance test at the 1% level. This result indicates that R&D investment is favorable for the IEE improvement. Technological progress is conducive to the innovation and improvement in energy conservation technology, thus enhancing IEE. R&D investment also leads to the development of new clean energy technologies, which promote the enhancement in IEE (Alam et al. 2019). W* X7 also has a positive and significant effect. The direct and indirect effects of R&D investment are significant.

The regression coefficient of urbanization is significantly positive. Shen et al. (2020) indicated that urbanization is the key to enhancing ecological factors for sustainable growth. Urbanization has an aggregation effect (Poumanyvong and Kaneko 2010). Urbanization promotes the redistribution of capital, technology, human resources, and other factors of production in space and is conducive to industrial agglomeration. Moreover, the spatial aggregation of production factors offers the possibility and convenience of knowledge and information spillovers, making the cost of technological innovation considerably reduced and promoting the improvement in advanced technology, such as clean production technology. Therefore, green and low-carbon industries are actively advocated for, which promotes the ecological transformation of industry and improves resource utilization efficiency. The indirect effect of urbanization is significant.

Based on the above results, we found that GDP has a positive impact on IEE in line with Wang et al. (2016) and Li et al. (2018). As for FDI, we demonstrated that FDI has a positive impact on IEE. This finding is supported by Blomström and Kokko (1998) and Li et al. (2018) and contradicted by Javorcik and Wei (2004) and the pollution haven hypothesis. The main reason for this may be the fact that China's industrial sector has strengthened the overall screening and supervision of foreign-funded enterprises. Accordingly, the introduction of foreign capital is conducive to the growth of the industrial economy. Besides, we pointed out the spatial spillover effect of different influencing factors. We found that not only economic development and industrial R&D investment are conducive to the improvement in local IEE but also have a positive impact on the improvement in IEE in neighboring provinces.

Conclusions and implications

Conclusions

As pollution emissions' reduction contributed to the improvement in a sustainable development capacity, China has gained popularity in controlling air pollution and establishing an environment-friendly society. This study measured and analyzed the spatial effects of IEE from 2007 to 2016 using the Super-SBM model. Based on the spatial factors, we presented a new empirical study and analysis of the industrial ecological environment.

The main results of the study are as follows. First, between 2007 and 2016, the average IEE of China showed a gradual upward trend, but there were substantial differences between the regions. IEE in the eastern region was the highest, whereas it was the lowest in the western region. The coastal geographical advantages and support of national policies led to a relatively high IEE in eastern China. Second, the spatial autocorrelation test showed that the spatial distribution of IEE is positively correlated, and the regions with a similar IEE present a geographic agglomeration trend. The geographical location had a significant impact on the spatial and temporal evolution of IEE. The spatial spillover effect is significant, demonstrating the characteristics of agglomeration in space. The high-high agglomeration type was concentrated in Liaoning, Jilin, and Inner Mongolia. These provinces need to take advantage of the spatial spillover effect. The low-low agglomeration type was mainly distributed in Gansu, Ningxia, and Sichuan, indicating that governmental support is the key to improving IEE in these areas. Lastly, according to the spatial Durbin panel model and spillover effect decomposition, it was shown that GDP, FDI, human capital, environmental governance investment, R&D investment, and urbanization have a positive impact on IEE. The industrial structure and energy consumption structure have a negative impact on IEE. In addition, GDP and R&D investment play a significant role in improving IEE in local and neighboring provinces.

Policy implications

Based on the above research conclusions, the following policy implications can be obtained:

First, it is necessary to propose a differentiation strategy to balance industrial economic growth and environmental protection. The high-quality IEE of the eastern region should be a benchmark for the other regions in China. The central and western regions should fully adopt the successful experience of the eastern region in improving IEE, especially in transforming industrial production patterns and promoting the application of environmental protection technologies to narrow the regional gap.

Second, the spatial spillover effects should be fully utilized. The results of spatial distribution characterization indicate that the spatial spillover effect is significant in high-high aggregation areas. Therefore, it is necessary to strengthen the leading role of high-concentration areas, such as Liaoning, Jilin, and Inner Mongolia, to accelerate the spillover of human resources, capital, technology, and other factors and to speed up the improvement in IEE locally and in surrounding areas. For low-low concentration areas, such as Sichuan, Guizhou, and Yunnan, IEE should be improved by reducing the consumption of high-pollution energies (e.g., coal) and promoting technology exchange and cooperation.

Third, a series of enhanced measures should be taken to improve IEE even further. Empirical regression results show that increases in GDP, FDI, human capital, environmental governance investment, R&D investment, and urbanization are effective in improving IEE. Therefore, FDI and talent introduction should be actively promoted. Industrial enterprises should be especially encouraged to increase investment in research and development of production technology and equipment to boost economic growth. Meanwhile, the transformation and upgrading of industrial development are to be accelerated, and the treatment of industrial pollution sources has to advance to reduce pollution emissions. Moreover, investment in the treatment of industrial pollution is recommended to be continuously strengthened, whereas the regulation of industrial pollution should be enhanced to improve IEE in the long term.

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