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Environmental quality assessment and spatial spillover effects of three urban agglomerations in China: A Meta-EBM approach

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ABSTRACT

The new development form of urban agglomeration has greatly promoted economic and social progress in recent years, but it is also facing severe environmental pollution problems. Understanding the status quo of environmental efficiency in urban agglomerations and its leading driving forces is an important prerequisite for formulating energy conservation and emission reduction policies. This research uses the Meta Epsilon Based Measure (Meta-EBM) model to measure the environmental emission efficiency of the Beijing-Tianjin-Hebei (BTH) , Yangtze River Delta (YRD) and Pearl River Delta (PRD) urban agglomerations in China from 2014 to 2018 so as to improve on the inability of traditional Data Envelopment Analysis (DEA) to combine linear and non-linear characteristics, and employs Moran's I index and spatial econometric methods to analyze their spatial dependence and main driving factors. The results demonstrate that the overall environmental efficiency of the three major urban agglomerations in the five years from 2014 to 2018 presents a wave-like development and then tends to be flat. The itemized efficiency of economic outputs has maintained a relatively high level with the environmental output index exhibiting the best efficiency for industrial wastewater, followed by industrial sulfur dioxide (SO_2). The scores of the two indicators for inhalable fine particle emissions ($PM_{2.5}$) and industrial smoke and dust in each urban agglomeration are not ideal, and there are obvious differences between regions. Among them, YRD and PRD are relatively inferior. From the perspective of spatial spillover effects, various indicators show diverse characteristics at different development stages of the regions. Population and Normalized Difference Vegetation Index (NDVI) have a positive effect on environmental efficiency, while both Gross Domestic Product (GDP) per capita and transportation tend to show greater negative effects on regional environmental optimization. This study proposes countermeasures as follows. Each urban agglomeration should set up measures suitable to local conditions and give full play to their location advantages.

Abbreviations: Meta Epsilon Based Measure, (Meta-EBM); Beijing-Tianjin-Hebei, (BTH) ; Yangtze River Delta, (YRD); Pearl River Delta, (PRD); Data Envelopment Analysis, (DEA); Sulfur dioxide, (SO_2); Inhalable fine particle emissions, ($PM_{2.5}$); Normalized Difference Vegetation Index, (NDVI); Gross Domestic Product, (GDP); Slacks-Based Measure, (SBM); Decision-Making Unit, (DMU); Volatile Organic Compounds, (VOCs); Foreign direct investment, (FDI); Industrialization level, (Indus); Spatial Dubin Model, (SDM); Spatial Autoregressive models, (SAR); Spatial Error Model, (SEM).

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They can also use space radiation to promote sector economic development and optimize urban environmental benefits.

1. Introduction

China has made tremendous economic and social achievements in the past few decades [1,2], leapfrogging Japan to become the world's second largest economy in 2010 [3], with China's total GDP in 2019 reaching 272 times that of 1978. Urban agglomerations have become a powerful engine for achieving economic development due to the increasing economic interactions between countries, the rapid circulation and exchange of various resources, and the clustering and joint development of cities within countries. From 2006 to 2015, the share of the 12 city clusters in the national GDP rose from 70.56% to 82.03%, with an average annual growth rate of more than 1% point. Among them, BTH, YRD and PRD have become highly representative world-class urban agglomerations, contributing more than 40% (40.85 trillion yuan) (2019), and becoming the focus of promoting the integrated development of major national regional strategies.

These three major urban agglomerations play a pivotal role in China's development, but their rapid expansion has led to a serious resource and environmental crisis in the three major urban agglomerations, as accelerated urbanization is closely linked to energy consumption. The three major urban agglomerations of BTH, YRD, and PRD have worrisome performance in terms of environmental quality such as water pollution and air pollution. In 2019, the south part of the Yangtze River and east area of the Yunnan-Guizhou Plateau became the main distribution regions of acid rain in China. Among the 165 water quality sections monitored in the Pearl River Basin, up to 3.0% are inferior at Grade V. The proportion of days for the average air quality exceeds the standard in the BTH region reached 46.9%, of which 4.9% were seriously polluted and 0.6% was severely polluted. The proportion of days for the average air quality exceeds the standard in the Yangtze region was 23.5%, accounting for 0.6% was severe pollution. Since the winter of 2012, extreme haze incidents in northern and eastern China, especially for BTH, YRD, PRD and other urban agglomerations have occurred one after another [4,5].

Considering the imbalance between economic development and the environment, this study aims to address the problems of tightening resource constraints, serious environmental pollution and ecosystem degradation, to continuously improve environmental efficiency, and to build a resource-saving and environment-friendly society in order to achieve sustainable urban development.

This study first uses the Meta-EBM model to evaluate environmental efficiency. Then the spatial autocorrelation model is used to consider the time lag effect and spatial lag effect of pollution from the perspective of spatial spillover. Finally, the interplay between urban cluster environments is explored by examining the relationship between geographical distance and spatial spillover effects. The research framework is shown in Fig. 1 below.

The contribution of this study is that by analyzing the spatial and temporal distribution patterns of environmental quality and efficiency assessment in China's three major urban agglomerations from 2014 to 2018, as well as exploring their main driving factors, it will, to a certain extent, provide a basis for relevant administrative departments to formulate policies related to improving the environmental quality of urban agglomerations, ultimately achieving a harmonious development between the environment and human socio-economic development of urban agglomerations, and providing referenceable suggestions for other urban agglomerations to improve their environmental conditions.

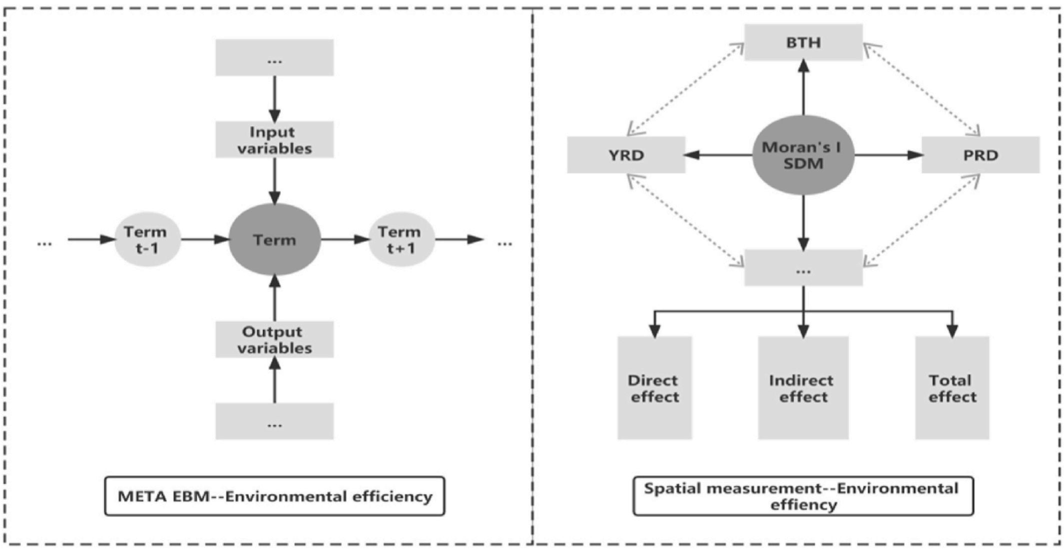


Fig. 1. The research framework.

2. Literature review

Under the dual challenges of the global climate crisis and the pressure of economic growth, the concepts of low-carbon development and green energy transition are now widely recognized by the international community [6]. Therefore, it is crucial to explore methods to evaluate the advantages and disadvantages of environmental and energy indicators.

Xia et al. [7] measured the environmental efficiency of China's mining industry based on China's inter-provincial data from 2007 to 2016. Wang et al. [8] analyzed the determinants of carbon emissions in the G20 countries from 2010 to 2015 based on the DEA-based hybrid measure model and meta-frontier analysis approach. Kounetas and Zervopoulos [9] used the meta-frontier framework to assess cross-border environmental performance. Bel and Holst [10] analyzed the influencing factors of air pollution in Mexico. Sun et al. [11] evaluated the analysis of optimal energy allocation and environmental performance of China's three major urban agglomerations. The empirical results demonstrate that China still has great potential in improving energy efficiency. Giannakitsidou et al. [12] used DEA to measure the environmental and circular economy performance of 26 EU countries, and the results showed poor performance by the old EU member states. Schlutow et al. [13] comprehensively assessed the integrity of Germany's atmospheric heavy metal deposits and ecosystems. Batsaikhan et al. [14] applied hydrochemical, environmental isotopic, and statistical approaches to assess groundwater pollution in Ulaanbaatar, Mongolia.

The inter-regional dependence and spatial spillover effects of different regions have a significant impact on China's inter-provincial economic development [15]. Ying [16] and Ying [17] tried to prove the expected diffusion effect of China's space economy from a core-periphery perspective. Brun et al. [18] divided China into coastal and non-coastal provinces to examine the interaction between coastal and inland provinces. Zhang and Felmingham [19] investigated the spatial spillover effects among the three major economic belts (East, Central, and West) based on the ideas of Brun, Combes, and Renard. Groenewold et al. [20]and Groenewold et al. [21] used the VAR model and found that the coastal and northwestern regions have a larger spillover effect on other regions. Chang [22] showed that spatial methods are effective for water quality management of non-point source pollution. Long et al. [23] focused on the spatial dependence and main driving factors of industrial carbon productivity. Ma et al. [24] analyzed the driving factors of haze in 152 cities of China by constructing a spatial economic weight matrix. Tang et al. [25] believed that China's haze pollution has strong spatial agglomeration and spatial spillover effects. Feng et al. [26] used the SDM framework based on STIRPAT to identify the socio-economic driving factors of pollution spillover heterogeneity, and explored the spatial spillover effects of environmental regulations on $PM_{2.5}$ concentration.

Combining the perspective of spatial measurement, Chuai et al. [27] believed that the level of economic development in the surrounding areas will lead to a certain regional correlation between energy consumption and carbon emissions. Elliott et al. [28] studied the relationship between the energy intensity of Chinese cities and the location of foreign companies. Rich [29] reported the link between air pollution and cardiopulmonary disease mortality and morbidity. Talbi [30] used a vector autoregressive model and found that the improvement of energy efficiency and fuel rate has a positive impact on the carbon emission reduction of the road transport sector in Tunisia. Lebreton et al. [31] quantified marine plastic pollution from both spatial and temporal aspects. Yan et al. [32] explored the spatial changes of $PM_{2.5}$ in the Beijing-Tianjin-Hebei region through spatial autocorrelation analysis.

The studies above have enriched our understanding of the emission efficiency of individual environmental pollutants, such as carbon emission efficiency, industrial wastewater emission efficiency, etc. While there are few studies evaluating efficiency by combining multiple pollution factors, a few scholars have evaluated environmental quality based on spatial measurement methods and analyzed its temporal and spatial distribution characteristics and influencing factors. Especially for the analysis of influencing factors, many studies have not considered the relationship of spatial interaction, and the relationship between related variables is based on the assumption of spatial autocorrelation. LeSage and Pace [33] pointed out that the characteristics of a local area will be affected to a certain extent by its neighboring areas. If one refers to Waldo Tobler's *First Law of Geography*, then the influence of spatial interaction cannot be ignored; otherwise, the simple use of traditional estimation methods may lead to deviations in the regression results obtained. Related studies have also shown that the significant spatial dependence of pollution emissions cannot be ignored [34].

In order to fill the above research gaps, this research shall evaluate the environmental quality and efficiency of the three major urban agglomerations in China from the perspective of spatial spillover effects and analyze their temporal and spatial distribution patterns of environmental quality and efficiency based on panel data from 2014 to 2018. This study is the first attempt to use spatial measurement methods to explore the environmental quality efficiency of the three major urban agglomerations in China and analyze its main driving factors. The goal is to provide a decision-making basis for the formulation of relevant policies that can improve the environmental quality of urban agglomerations to a certain extent.

Compared with the existing literature, this study has three innovations. First, the Meta-EBM DEA model is selected to take into account the technical level differences between different groups, while also overcoming the defect of the traditional DEA model that does not combine linear and non-linear dual characteristics. Second, the selection of input-output indicators is more reasonable and comprehensive. The four environmental output indicators of SO_2, industrial smoke and dust emissions, waste water discharged, and $PM_{2.5}$ combine traditional pollutants with newer pollutants and are closer to the current environmental quality status of China's three major urban agglomerations. Third, different from previous studies that ignore the spatial dependence of urban agglomeration environmental efficiency, this research adds Moran's I index of spatial metrology and spatial spillover effect analysis in the second-stage empirical link to provide the space-time distribution pattern and driving factors that support the first-stage environmental efficiency. Therefore, this article will contribute to the innovative perspectives and achievements of environmental efficiency evaluation and spatial effect research of typical urban agglomerations in China.

3. Research methods

3.1. Meta-EBM DEA model

Traditional DEA models can be divided into radial DEA models (represented by A. Charnes & W. W. Cooper & E. Rhodes (CCR) and Banker & Charnes & Cooper (BCC)) and non-radial DEA models (represented by Slacks-Based Measure (SBM)). However, these models fail to consider the possibility of the simultaneous existence of radial and non-radial features. Therefore, Tone and Tsutsui [35] proposed the EBM model, which considers the combination of radial and non-radial features.

The 60 cities in the three major urban agglomerations of China's YRD, BTH, and PRD selected in this study have different social cultures, economic environments, production structures, etc., and it would be unfair to use traditional DEA methods with the same technical level when evaluating their efficiency. Portela and Thanassoulis [36] put forward the concept of convex meta-frontier, and pointed out in a certain period of time that the technology of all groups and the output level of production with advanced technology will be further improved through technical exchanges between groups, which then expand the production boundary outward to improve operating performance. O'Donnell et al. [37] formally proposed a Meta-frontier model that can accurately calculate group and common technical efficiency. This research also uses meta-frontier analysis (curve QQ'), which is an envelope curve (Fig. 2) that includes the production frontiers of all groups, so that the three major urban agglomerations (curves 11′, 22′, and 33′) can have their efficiency measured under a common benchmark.

Based on the relevant analysis of the above EBM model and Meta-frontier model, this research proposes a Meta-EBM DEA model that combines the advantages of the two, and incorporates many characteristics such as radial, non-radial, and group differences into the model. The specific process of the Meta-EBM DEA model runs as follows.

Due to differences in resources, regulations, and environment and management modes, it is assumed that all research objects (N) are composed of decision-making units of g groups ($N=N_1+N_2+N_3+N_G$), and x_{ij} and y_{rj} respectively represent the i^{-th} input ($i = 1, \ldots m$) of the j^{-th} unit ($j = 1, \ldots N$) and the final output of the r^{-th} unit ($r = 1, \ldots s$) . θ and η are linear inputs and linear outputs, respectively. w_i^- and w_i^+ are the weight of i inputs and outputs, respectively. s_i^- and s_i^+ are the gap slack and excess slack, respectively. $\mathcal{E}_x$ and $\mathcal{E}_y$ are Linear and nonlinear combination. λ is the weight of the input-output term. λ_{jg} represent the weight of decision-making units in all groups. λ_{ij} represent the weight of i^{-th} input ($i = 1, \ldots m$) of the j^{-th} unit. Under the common boundary, decision-making unit k can choose the most favorable final output weight to maximize its efficiency value. Therefore, in the undirected Meta-EBM DEA model, the efficiency of decision-making unit k is solved by the following linear programming formula (1):

$$\min_{0,\eta,\lambda,s^-,s^+} \frac{\theta - \mathcal{E}_x \sum_{g=1}^{G} \sum_{i=1}^{m} \frac{w_i^- s_i^-}{X_{i0}}}{\eta - \mathcal{E}_y \sum_{g=1}^{G} \sum_{i=1}^{S} \frac{w_i^+ s_i^+}{Y_{i0}}} \tag{1}$$

The constraint conditions are the following formula (2)-(7):

$$X_{io} = \sum_{g=1}^{G} \sum_{j=1}^{n} X_{ijg}\theta_{jg} + S_i^- (i = 1, \ldots m) \tag{2}$$

$$Y_{io} = \sum_{g=1}^{G} \sum_{j=1}^{n} Y_{ijg}\eta_{jg} - S_i^+ (i = 1, \ldots s) \tag{3}$$

$$\sum_{g=1}^{G} \sum_{j=1}^{n} \lambda_{jg} = 1 \tag{4}$$

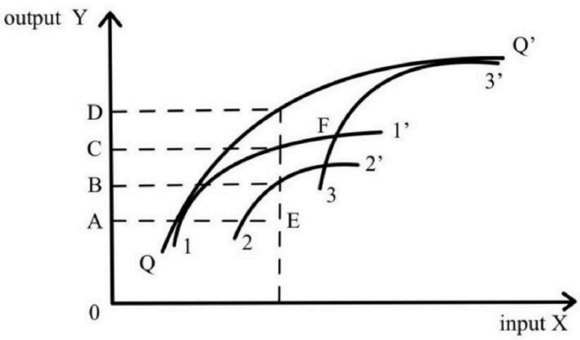


Fig. 2. Meta-frontier curve.

$$\theta X_0 - X_\lambda - S^- = 0, \eta Y_0 - Y_\lambda + S^+ = 0 \tag{5}$$

$$\lambda_1 + \lambda_2 + \ldots + \lambda_n = 1 \tag{6}$$

$$\lambda_{ij} \geq 0, s_i^- \geq 0, s_i^+ \geq 0 \tag{7}$$

Two indicators can be obtained according to the input distance function: ① Calculate the input distance function value of the Decision-Making Unit (DMU) in the group according to the efficiency frontier of the g-th group - namely, β^g. ② Calculate the input distance function value of each DMU according to the common boundary – namely, β^m. Therefore, two different technical efficiencies can be calculated for the two different boundaries: the technical efficiency of the common boundary under the common boundary is $TE^m = D^m(y,x)$; and the group technical efficiency under the specific g group boundary is $TE^g = D^g(y,x)$, where $D^m(y,x) \geq D^g(y,x)$, which means that the g-th group is included in the common boundary, and so there is a common technology between the two. Therefore, the meta technical ratio (MTR) of each DMU in the g-th group is shown in formula (8):

$$MTR^g = \frac{D^m(y,x)}{D^g(y,x)} = \frac{TE^m}{TE^g} = \frac{1-\beta^m}{1-\beta^g} \tag{8}$$

The technology gap ratio (TGR) of the g-th group is shown in formula (9):

$$TGR^g = \frac{TE^m(x,y)}{TE^g(x,y)} \tag{9}$$

3.2. Spatial autocorrelation model

The spatial panel model simultaneously captures the characteristic changes of the observation unit in space and time. An explanation of the space lag, space error, and space Doberman model may be needed. Before setting a specific spatial measurement model for estimation, it is necessary to confirm the existence of spatial correlation, and Moran index statistics are generally constructed for verification.

$$y_{it} = \rho W_i' y_t + X_{it}'\beta + \mu_i(optional) + \xi_t \ (optional) + \varepsilon_{it} \tag{10}$$

$$y_{it} = X_{it}' \beta + \mu_i \ (optional) + \xi_t(optional) + \varphi_{it} \tag{11}$$

$$\varphi_{it} = \lambda \sum_{j=1}^{N} W_{ij}\varphi_{ij} + \varepsilon_{ij} \tag{12}$$

$$y_{it} = \rho \sum W_{ij}\, y_{ij} + X_{it}' \beta + \rho \sum W_{ij}\, X_{ijt} + \mu_i \ (optional) + \xi_t(optional) + \varepsilon_{it} \tag{13}$$

In formula (10) and (11), y_{it} is the explained variable of the observation unit i at time t. ρ is the spatial autoregressive coefficient of dependent variable. $W_i' y_t$ is the spatial interaction term between y_{it} and its neighboring unit. $X'it$ is the i-th row of the explanatory variable. β is the i-th row of the regression coefficient vector. ε_{it} is the error term.

In formula (12), λ is the autocorrelation coefficient of the spatial disturbance term. W_{ij} is the preset non-zero $N \times N$-order spatial matrix. ε_{ij} is the error term.

In formula (13), the spatial Durbin model can be used to test the hypotheses of: H_0: $\theta = 0$ and H_1: $\theta + \rho\beta = 0$. The first hypothesis H_0 examines whether the spatial Dubin model can be reduced to a spatial lag model, while the second hypothesis examines H_1 whether it can be reduced to a spatial error model Elhorst [38]. μ_i and ξ_t correspond to space and time effects, respectively. If both hypotheses are rejected, then the spatial Dubin model can better describe the spatial spillover effects of environmental governance.

3.3. Data sources and description

For the measurement of environmental efficiency in regional economic growth, environmental indicators must be combined with other production factors so that they can be correlated. We select data from 2014 to 2018, covering a total of 60 cities in BTH, YRD and PRD. Referring to the input and output indicators of Cui et al. [39] and Du et al. [40], we choose labor, energy consumption and fixed assets as input variables, and GDP, SO_2, $PM_{2.5}$, industrial smoke and dust emissions and waste water discharged as output variables. Labor, energy consumption and fixed assets are important factors contributing to economic growth; GDP reflects the final outcome of production activities of all resident units in the city over a certain period of time, while the amount of pollutant emissions such as SO_2, $PM_{2.5}$, industrial smoke and dust emissions and waste water discharged indicate the extent to which the production and demand acquisition behavior of the region affects the surrounding water and air environment, and is a direct cause of ecological change. The description of the specific input-output variables in Table 1.

3.3.1. Input variables

Labor: Refers to planned total investment of 5 million yuan or more in construction projects and real estate development

Table 1
Input and output variables and data sources.

Input variable	Output variable	Data source
Labor Energy consumption Fixed assets	GDP SO_2 $PM_{2.5}$ Industrial smoke and dust emissions Waste water discharged	From 2014 to 2018 in China City Statistical Yearbook and the statistical yearbook of each city, the air pollutant data partly come from the reports of the environmental protection bureau of each province and city and the air quality monitoring website.

investments by various registered enterprises, institutions, administrative units and urban self-employed, both in urban and rural areas, including the original standard of urban fixed asset investment plus the investment of rural enterprises and institutions, which have been in use since 2011. Unit: million people.

Energy consumption: The energy consumption of industrial enterprises includes the energy used by industrial enterprises from fuel, power, raw materials and auxiliary materials in the production process, as well as process energy and non-production energy; for an energy processing and conversion enterprise, it also includes the input of energy processing and conversion. Unit: tons of standard coal.

Fixed assets: Refers to planned total investment of 5 million yuan or more in construction projects and real estate development investments by various registered enterprises, institutions, administrative units and urban self-employed, both in urban and rural areas, including the original standard of urban fixed assets investment plus the investment of rural enterprises and institutions, which have been in use since 2011. Fixed assets in this paper refer to the amount of investment and are not a concept of capital stock. Unit: 10,000 yuan.

3.3.2. Output variables

GDP: Refers to the final result of production activities of all resident units in a country (or region) in a certain period of time calculated according to the national market price, and is often recognized as the best indicator to measure a country's economic situation. GDP is an important comprehensive statistical index in the accounting system and the core index in China's new national economic accounting system. It reflects the economic strength and market size of a country (or region). Unit: 10,000 yuan.

SO_2: The amount of sulfur dioxide discharged into the atmosphere by enterprises during fuel combustion and production processes. Unit: ton.

$PM_{2.5}$: Fine particles refer to those with aerodynamic equivalent diameter less than or equal to 2.5 μm in ambient air. They can be suspended in the air for a long time. The higher their concentration in the air is, the more serious is the air pollution. Compared to coarser atmospheric particles, $PM_{2.5}$ has a small particle size, large area, strong activity, easy attachment of toxic and harmful substances (e.g., heavy metals, microorganisms, etc.), long residence time in the atmosphere and long transportation distance, thus having greater impact on human health and atmospheric environmental quality. Unit: $\mu g/m^3$.

Industrial smoke and dust emissions: Industrial smoke and dust emissions refer to the weight of particulate matter emitted by enterprises in the production process, such as refractory dust of iron and steel enterprises, dust of coke screening systems of coking enterprises, dust of sintering machines, dust of lime kilns, cement dust of building materials enterprises, etc. They do not include smoke and dust discharged into the atmosphere from power plants. Unit: ton.

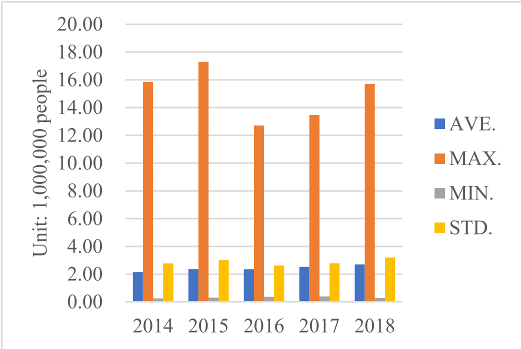
Waste water discharged: Waste water discharged includes production waste water, production waste water, and cooling water. It refers to waste water and waste liquid produced in the industrial production process, which contains industrial production materials, intermediate products, by-products, and pollutants produced in the production process. There are many kinds of waste water discharged and their composition is complex. Unit: 10,000 tons.

4. Results

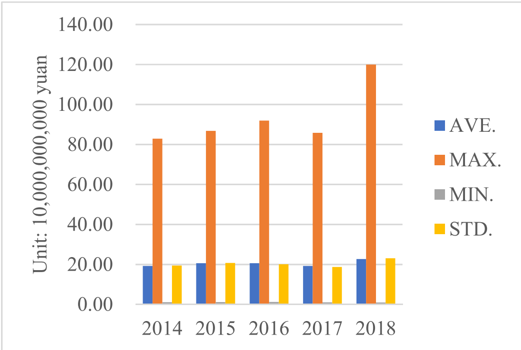
4.1. Statistical analysis

Fig. 3(a–c) shows the overall status of the data for the three input indicators of employment population, total fixed assets and total energy consumption for the 60 cities from 2014 to 2018, as Fig. 3(a) shows the mean, maximum and minimum values as well as the standard deviation of the employment population values for each year for the 60 cities. The average number of employees decreased slightly in 2016 compared with the previous year, and there has been an overall growth trend over the past five years. In 2018, the annual average urban employment population increased by 25.17% compared with 2014. The average value of fixed assets in the five-year period showed a growth state, but then significantly declined in 2017, even lower than the 2014 average, but the index value then rose sharply in 2018, reaching 17.63% compared to the previous year. The total energy consumption of the three major urban agglomerations from 2014 to 2017 basically has maintained the same level, and statistics such as the maximum, minimum, and mean in 2018 al l dropped significantly, while overall investment in total energy consumption has also fallen. The above analysis shows that the total energy input, urban employment, and fixed assets of urban agglomerations have risen overall. Total energy consumption increased first and then decreased, showing an unstable trend.

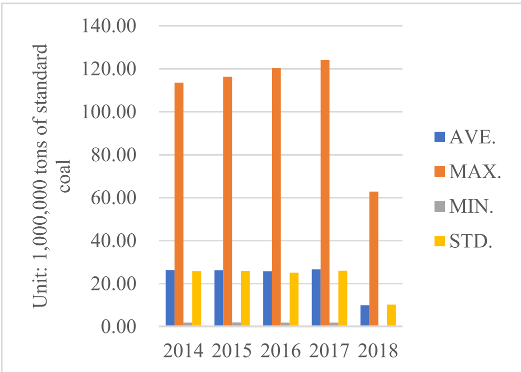
Fig. 4(a–e) show the statistics of total city's five output indicators: GDP, industrial SO_2 emissions, industrial wastewater, annual



a. Statistical analysis of employed population for total cities.



b. Statistical analysis of total fixed assets for total cities.



c. Statistical analysis of total energy consumption for total cities.

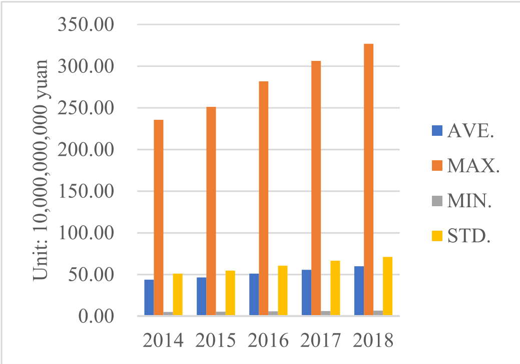
Fig. 3. a. Statistical analysis of employed population for total cities. b. Statistical analysis of total fixed assets for total cities. c. Statistical analysis of total energy consumption for total cities.

average concentration of $PM_{2.5}$, and industrial smoke and dust emissions. In general, the average GDP output value has been increasing year by year, while industrial SO_2 emissions, industrial wastewater, and annual average concentration of $PM_{2.5}$ have shown a steady downward trend, of which the index value of $PM_{2.5}$ has significantly decreased the most. However, the average emissions of industrial smoke and dust reach the peak in 2015 and decline significantly in the following year, followed by a gradual decline. This shows that urban agglomerations are paying attention to the unfavorable factors of environmental changes such as sewage and air pollution in the process of urban economic development, and have achieved obvious results in environmental governance and protection year by year. Industrial smoke and dust indicators increased significantly in 2015, rising 19, 391 tons compared to 2014, but fell sharply in 2016 by 58.03%, and have showed a steady decline year by year from 2016 to 2018.

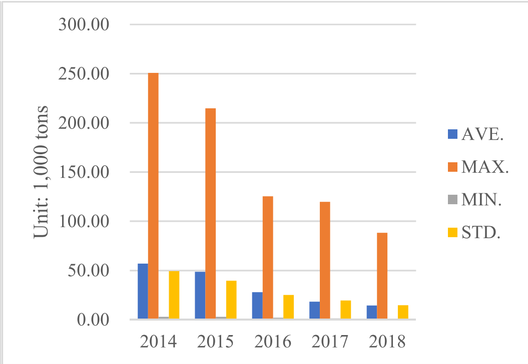
4.2. Environmental quality assessment results

4.2.1. Analysis of total efficiency

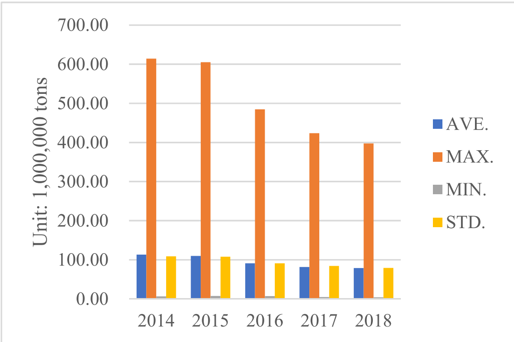
Fig. 5 presents the chart of the trend change in the total efficiency score of each urban agglomeration from 2014 to 2018. Overall, the environmental quality efficiency of the three major urban agglomerations shows fluctuating development that is gradually



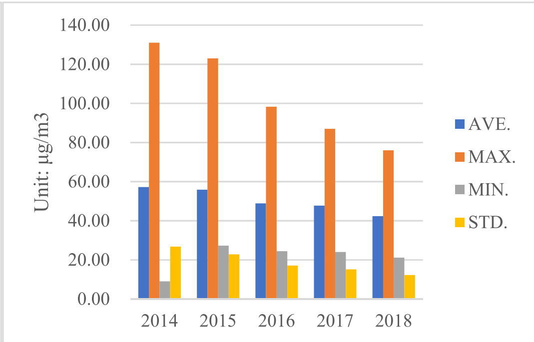
a. Statistical analysis of GDP for total cities.



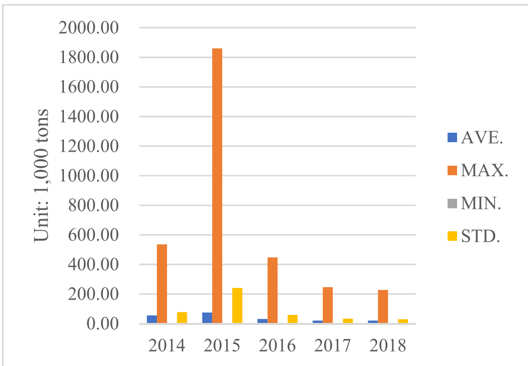
b. Statistical analysis of SO_2 for total cities.



c. Statistical analysis of waste-water discharged for total cities.



d. Statistical analysis of $PM_{2.5}$ for total cities.



e. Statistical analysis of industrial smoke and dust emissions for total cities.

Fig. 4. a. Statistical analysis of GDP for total cities. b. Statistical analysis of SO_2 for total cities.
c. Statistical analysis of waste-water discharged for total cities. d. Statistical analysis of $PM_{2.5}$ for total cities. e. Statistical analysis of industrial smoke and dust emissions for total cities.

converging.

In the first three years, each urban agglomeration experienced significant changes. The environmental quality efficiency of the YRD, BTH, and PRD urban agglomerations experienced a decrease of 31.35%, 20.20%, and 49.12%, respectively, in 2015, returning to normal in 2016. It shows that the three major urban agglomerations neglected environmental governance and protection while developing their economy in the early stage, and environmental benefits fell significantly. In March 2015, China implemented the *Opinions on Accelerating the Construction of Ecological Civilization*, clarifying that the construction of an ecological civilization will inject a new impetus into energy conservation and emission reduction. The above results show that the improvement of these governance plans and measures has played an important role in the gradual adjustment of environment-ecologic efficiency and maintaining it at a relatively normal threshold. From 2014 to 2016, the environmental efficiency of the BTH was significantly better than that of the YRD

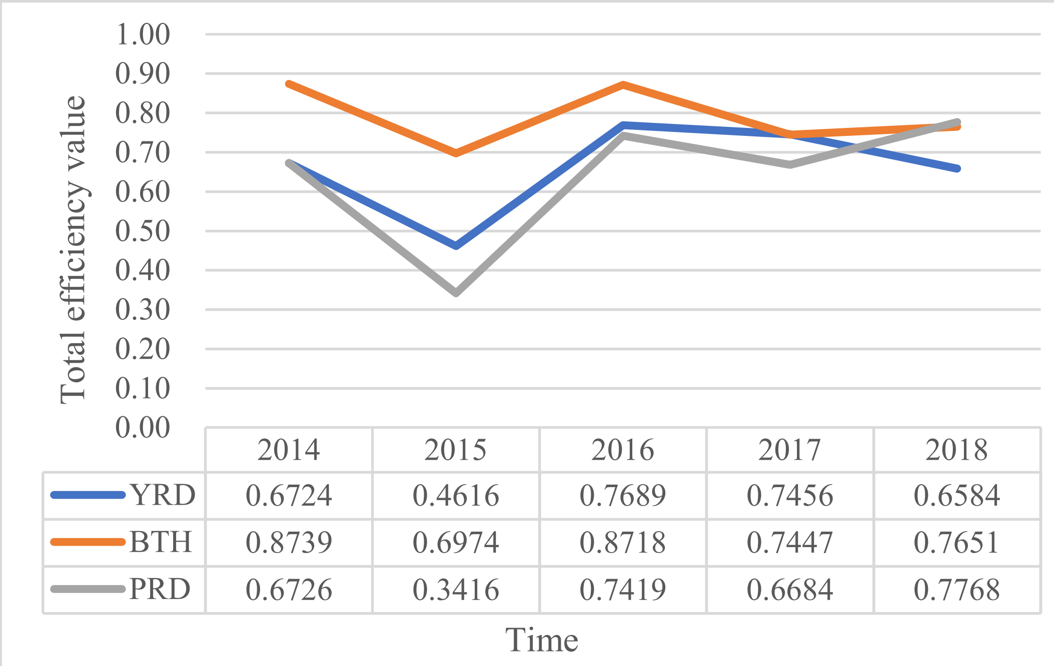


Fig. 5. Comparison chart of trend change of the total efficiency score of each urban agglomeration from 2014 to 2018.

and PRD, but the trend line showed a slight decline. This is due to the symposium hosted by General Secretary Xi Jinping in Beijing in 2014, which clearly identified the realization of the synergistic development of BTH as a major national strategy, and the adoption of the BTH Synergistic Development Plan Outline in 2015, which identifies the integration of transportation, ecological and environmental protection, and the upgrading and transfer of industries in BTH as key areas. The PRD continued to be at a disadvantage during 2014–2017, but it rose to be the best among the three major urban agglomerations in 2018. From 2016 to 2018, the environmental efficiency of the three urban agglomerations gradually tended to be the same. Except for the YRD that declined year by year since 2016, the BTH and YRD both increased in 2018 after declining, and their environmental efficiency values are almost unanimous. It shows that among the three urban agglomerations, the BTH has the best environmental governance effect, where the PRD's environmental governance level is in a weak position, but by continuing to pay attention and actively improve in the following years, its environmental governance effect has been significantly optimized. The YRD still lacks the proper attention paid to the environment.

Table 2 shows the environmental efficiency of the three major urban agglomerations. In the three urban agglomerations, there is a total of 60 cities, of which Huangshan, Qinhuangdao, Tangshan, and Tongling have an average environmental quality of 1. It shows that their environmental efficiency value is relatively strong, their degree of urban energy utilization is high, and the management and protection of the ecological environment is being properly emphasized while the urban industry is developing.

The two cities of Huangshan and Tongling belong to the YRD, accounting for 6.25% of the urban agglomeration area. Within the YRD, 22 cities, including Bengbu and Changzhou have scores of environmental efficiencies greater than 0.6, accounting for 68.75% of the area, and the overall environment is in good condition. The five-year evaluation scores of Shanghai are less than 0.3, of which the average environmental efficiency score of Shanghai is only 0.2300, and its minimum goes as low as 0.1837. Bengbu, Changzhou, Chizhou, Bozhou, Ma'anshan, and Shaoxing had low efficiency scores in the past few years, but their efficiency scores hit 1 later, indicating that these cities were weak in the efficiency of energy input and output in the early stage, but attention to and protection of ecological development and the environment were strengthened in the later stage. Hefei, Xuancheng, and Lu'an scored 1 in environmental assessment efficiency in 2014, but their scores declined in 2015–2018.

The two cities of Qinhuangdao and Tangshan belong to the BTH, accounting for approximately 15.38% of its area. In the region, there are 12 cities with an average score of environmental efficiency greater than 0.6, including Beijing and Cangzhou, accounting for 92.31%, which is the best among the three urban agglomerations. In 2015, 8 cities including Beijing, Hengshui, and Qinhuangdao scored 1, and the number of cities with a score of 1 accounted for 61.54% of the total number of urban agglomerations, thus becoming the best of the three major urban agglomerations that year.

There is no city in the PRD with an environmental efficiency score of 1, and its overall average is 0.6403. Among them, 9 cities, including Guangzhou and Jiangmen, have an efficiency score greater than 0.6, and the number of cities with a score greater than 0.6 accounts for 60% of the total number of cities in the urban agglomeration, and Zhaoqing has an efficiency score of 0.9290, which is the best in the PRD. The lowest is Huizhou with an efficiency score of less than 0.3. Guangzhou and Yunfu's scores fell 97.65% and 92.23%, respectively, in 2015, and they were the cities with the most obvious decline in the region. In 2014, Shenzhen's environmental efficiency score was 0.0439, ranking last in the PRD. However, Shenzhen's efficiency score hit 1 in 2015 for a growth rate of 2177.90%.

Table 2
Environmental efficiency scores and changes in ranking for each city in BTH, YRD and PRD from 2014 to 2018.

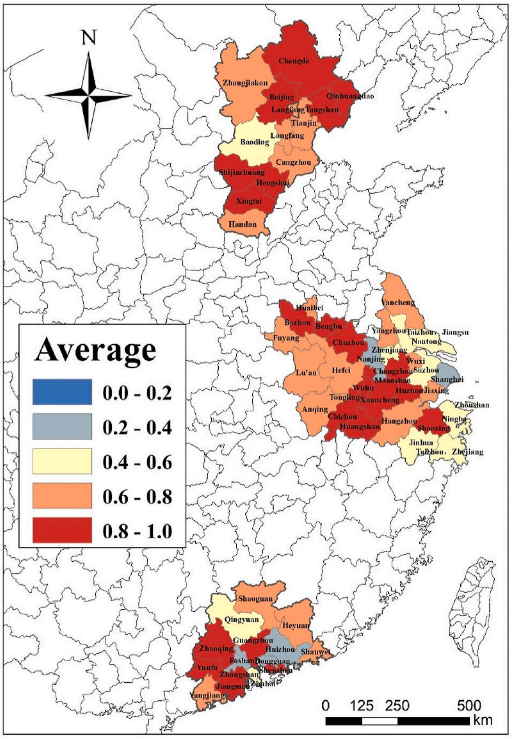
Region	No.	DMU	2014		2015		2016		2017		2018		Average	
			Rank	Score	Rank	Score	Rank	Score	Rank	Score	Rank	Score	Rank	Score
BTH	1	Beijing	1	1.0000	1	1.0000	1	1.0000	1	1.0000	60↓	0.0864	20	0.8173
	2	Tianjin	45	0.4990	1↑	1.0000	31↓	0.8419	53↓	0.4034	1↑	1.0000	26	0.7489
	3	Baoding	25	0.8248	54↓	0.1067	43↑	0.6354	39↑	0.6258	36↑	0.5630	46	0.5511
	4	Tangshan	1	1.0000	1	1.0000	1	1.0000	1	1.0000	1	1.0000	1	1.0000
	5	Langfang	23	0.8588	50↓	0.1791	27↑	0.8765	35↓	0.6694	1↑	1.0000	32	0.7168
	6	Shijiazhuang	21	0.8853	1↑	1.0000	1	1.0000	43↓	0.5825	1↑	1.0000	14	0.8936
	7	Handan	1	1.0000	48↓	0.1926	47↑	0.5792	32↑	0.7210	28↑	0.7438	38	0.6473
	8	Qinhuangdao	1	1.0000	1	1.0000	1	1.0000	1	1.0000	1	1.0000	1	1.0000
	9	Zhangjiakou	36	0.6543	1↑	1.0000	29↓	0.8574	37↓	0.6561	38↓	0.5305	29	0.7397
	10	Chengde	1	1.0000	46↓	0.2227	1↑	1.0000	1	1.0000	1	1.0000	18	0.8445
	11	Cangzhou	37	0.6390	43	0.3656	50	0.5435	47	0.5079	1↑	1.0000	42	0.6112
	12	Xingtai	1	1.0000	1	1.0000	1	1.0000	22↑	0.9085	35↓	0.5832	13	0.8983
	13	Hengshui	1	1.0000	1	1.0000	1	1.0000	40↓	0.6066	45↓	0.4391	22	0.8091
YRD	1	Shanghai	59	0.1837	49↓	0.1837	60↓	0.2975	59↑	0.2975	59	0.1876	60	0.2300
	2	Nanjing	52	0.4079	40↑	0.4079	58↓	0.3527	57↑	0.3527	57	0.2834	57	0.3609
	3	Wuxi	47	0.4935	36↑	0.4935	28↑	0.8581	24↑	0.8581	1↑	1.0000	28	0.7406
	4	Changzhou	1	1.0000	60↓	0.0236	1↑	1.0000	1	1.0000	1	1.0000	24	0.8047
	5	Suzhou	58	0.3020	44↑	0.3020	49↓	0.5551	44↑	0.5551	53	0.3009	55	0.4030
	6	Nantong	46	0.4971	35↑	0.4971	44↓	0.5902	41↑	0.5902	52↓	0.3307	50	0.5010
	7	Yancheng	40	0.5736	30↑	0.5736	1↑	1.0000	1	1.0000	37↓	0.5585	27	0.7411
	8	Yangzhou	38	0.5999	29↑	0.5999	40↓	0.6853	34↑	0.6853	33↑	0.6232	39	0.6387
	9	Zhenjiang	42	0.5325	32↑	0.5325	33↓	0.7925	28↑	0.7925	56↓	0.2926	45	0.5885
	10	Taizhou，Jiangsu	48	0.4812	37↑	0.4812	53↓	0.4934	49	0.4934	46	0.4086	51	0.4716
	11	Hangzhou	54	0.3925	42↑	0.3925	1↑	1.0000	1	1.0000	42↓	0.4836	37	0.6537
	12	Ningbo	53	0.3967	41↑	0.3967	54↓	0.4694	51↑	0.4694	51	0.3464	53	0.4157
	13	Jiaxing	32	0.7213	26↑	0.7213	1↑	1.0000	1	1.0000	58↓	0.2164	31	0.7318
	14	Huzhou	29	0.7658	24↑	0.7658	26↓	0.9077	23↑	0.9077	27↓	0.7505	19	0.8195
	15	Shaoxing	33	0.7028	27↓	0.7028	1↓	1.0000	1	1.0000	1	1.0000	15	0.8811
	16	Jinhua	41	0.5550	31↓	0.5550	51↓	0.5430	45↓	0.5430	41↓	0.4959	47	0.5384
	17	Zhoushan	44	0.5004	34↑	0.5004	59↓	0.3445	58↑	0.3445	34↑	0.5950	52	0.4570
	18	Taizhou，Zhejiang	48	0.4812	37↑	0.4812	53↓	0.4934	49↑	0.4934	46↑	0.4086	51	0.4716
	19	Hefei	1	1.0000	1	1.0000	45↓	0.5870	42↑	0.5870	47↓	0.3885	33	0.7125
	20	Wuhu	1	1.0000	1	1.0000	1	1.0000	1	1.0000	24↓	0.8865	5	0.9773
	21	Bengbu	30	0.7490	25↑	0.7490	1↑	1.0000	1	1.0000	1	1.0000	12	0.8996
	22	Maanshan	20	0.9097	21↓	0.9097	1↑	1.0000	1	1.0000	1	1.0000	6	0.9639
	23	Huaibei	43	0.5261	33↑	0.5261	1↑	1.0000	1	1.0000	31↓	0.6446	30	0.7394
	24	Tongling	1	1.0000	1	1.0000	1	1.0000	1	1.0000	1	1.0000	1	1.0000
	25	Anqing	35	0.6578	28↑	0.6578	36↓	0.7550	30↑	0.7550	39↓	0.5104	36	0.6672
	26	Huangshan	1	1.0000	1	1.0000	1	1.0000	1	1.0000	1	1.0000	1	1.0000
	27	Chuzhou	1	1.0000	1	1.0000	30↓	0.8500	25↑	0.8500	1↑	1.0000	7	0.9400
	28	Fuyang	49	0.4745	38↑	0.4745	42↓	0.6582	36↑	0.6582	26↑	0.7796	43	0.6090
	29	Lu'an	1	1.0000	1	1.0000	52↓	0.5424	46↑	0.5424	54↓	0.2974	35	0.6765
	30	Bozhou	27	0.7912	23↓	0.7912	1↑	1.0000	1	1.0000	1	1.0000	10	0.9165
	31	Chizhou	24	0.8274	22↓	0.8274	1↓	1.0000	1	1.0000	1	1.0000	8	0.9309
	32	Xuancheng	1	1.0000	1	1.0000	32↓	0.8068	27↑	0.8068	30↓	0.6894	17	0.8606
PRD	1	Guangzhou	1	1.0000	60↓	0.0236	1↑	1.0000	1	1.0000	1	1.0000	24	0.8047
	2	Foshan	56	0.3846	56	0.0623	41↑	0.6650	56↓	0.3580	50↑	0.3580	56	0.3656
	3	Zhaoqing	31	0.7274	1↑	1.0000	25↓	0.9176	1↑	1.0000	1	1.0000	9	0.9290

(continued on next page)

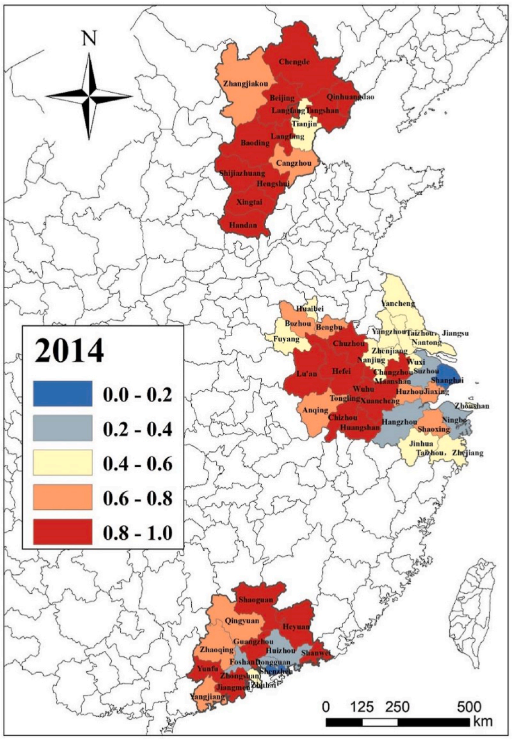
Table 2 (*continued*)

Region	No.	DMU	2014		2015		2016		2017		2018		Average	
			Rank	Score	Rank	Score	Rank	Score	Rank	Score	Rank	Score	Rank	Score
	4	Shaoguan	26	0.8017	52↓	0.1333	1↑	1.0000	1	1.0000	1	1.0000	25	0.7870
	5	Qingyuan	34	0.6617	45↓	0.2257	35↑	0.7736	50↓	0.4810	43↑	0.4810	48	0.5246
	6	Yunfu	1	1.0000	55↓	0.0777	1↑	1.0000	1	1.0000	1	1.0000	21	0.8155
	7	Shenzhen	60	0.0439	1↑	1.0000	1	1.0000	1	1.0000	1	1.0000	23	0.8088
	8	Dongguan	55	0.3912	58↓	0.0357	55↑	0.4171	55	0.3689	49↑	0.3689	58	0.3164
	9	Huizhou	57	0.3631	59↓	0.0336	56↑	0.3970	60↓	0.2927	55↑	0.2927	59	0.2758
	10	Shanwei	22	0.8735	1↑	1.0000	57↓	0.3932	54↑	0.3884	48↑	0.3884	44	0.6087
	11	Heyuan	1	1.0000	57↓	0.0584	1↑	1.0000	48↓	0.5073	40↑	0.5073	41	0.6146
	12	Zhuhai	39	0.5808	51↓	0.1649	48↑	0.5595	38↑	0.6413	32↑	0.6413	49	0.5176
	13	Zhongshan	51	0.4720	53↓	0.1073	46↑	0.5858	52↓	0.4523	44↑	0.4523	54	0.4139
	14	Jiangmen	1	1.0000	1	1.0000	38↓	0.7163	26↑	0.8286	25↑	0.8286	16	0.8747
	15	Yangjiang	28	0.7898	47↓	0.2021	39↑	0.7034	33↑	0.7071	29↑	0.7071	40	0.6219

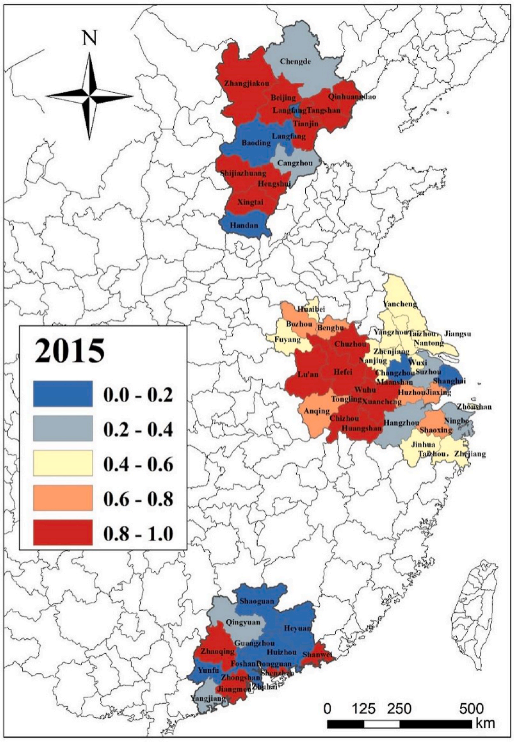
Note: The ↑/↓ indicates that this city's environmental efficiency score ranking is up/down compared to the previous year.



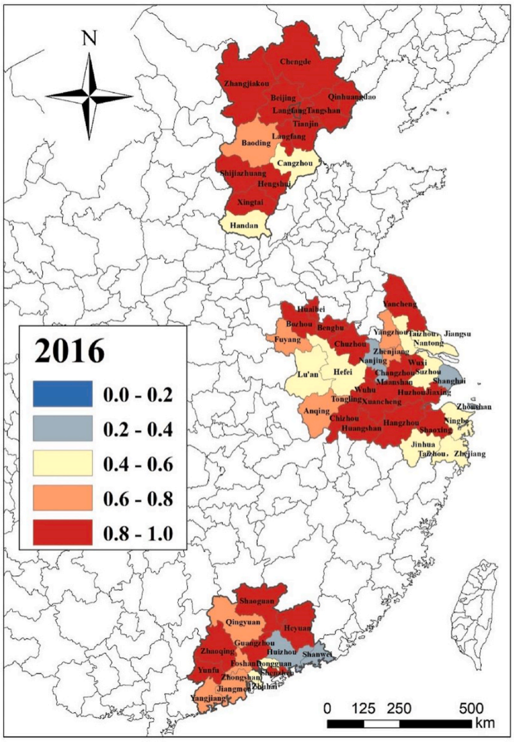
a Average environmental efficiency values for each city from 2014-2018.



b Distribution of environmental efficiency scores in 2014.

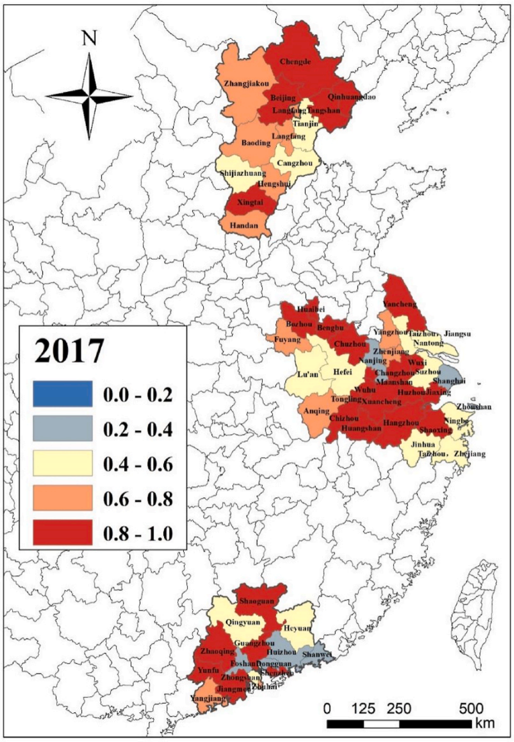


c. Distribution of environmental efficiency scores in 2015.

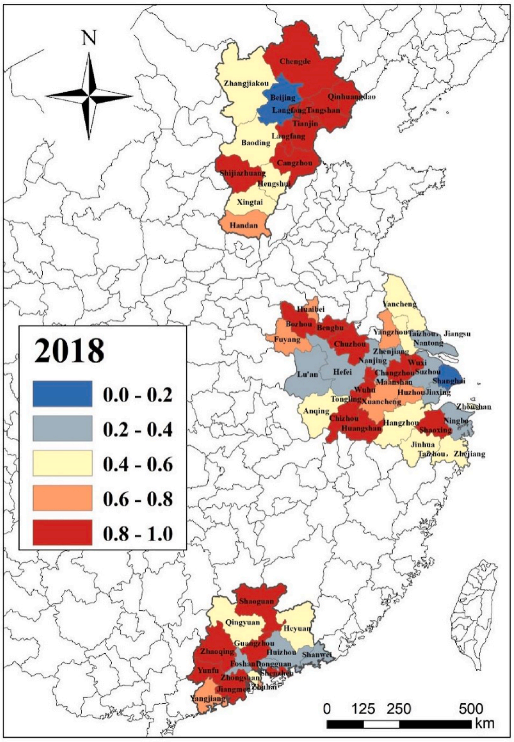


d. Distribution of environmental efficiency scores in 2016.

Fig. 6. a. Average environmental efficiency values for each city from 2014 to 2018. b. Distribution of environmental efficiency scores in 2014. c. Distribution of environmental efficiency scores in 2015. d. Distribution of environmental efficiency scores in 2016. e. Distribution of environmental efficiency scores in 2017. f. Distribution of environmental efficiency scores in 2018.



e. Distribution of environmental efficiency scores in 2017.



f. Distribution of environmental efficiency scores in 2018.

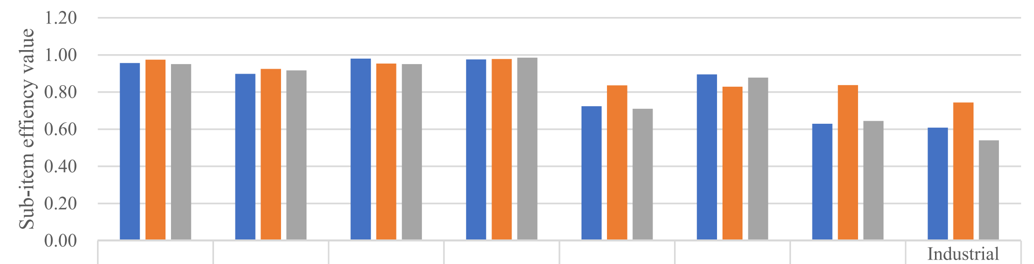
Fig. 6. (*continued*).

To better show the spatial pattern and temporal variation of environmental efficiency scores across cities, we plotted Fig. 6(a–f). Fig. 6(a) shows the average environmental efficiency score across cities from 2014 to 2018, and it is easy to see that a large proportion of cities have an average environmental efficiency above 0.6, showing a good level of environmental performance. Only five cities have an average environmental efficiency between 0.2 and 0.4. However, in terms of individual years, the environmental efficiency of cities varies considerably, as evidenced by the concentration of cities with high environmental efficiency and, correspondingly, low environmental efficiency. In order to explore the reasons for this and the influencing factors, we conduct a spatial spillover analysis of environmental efficiency later in the paper.

In terms of individual city clusters, (1) Within the BTH, the cities of Qinhuangdao and Tangshan have maintained high levels of environmental efficiency from 2014 to 2018. Over time, cities with high levels of environmental efficiency have gradually shifted from inland to coastal cities, such as Tianjin, Cangzhou and Langfang. (2) The level of environmental efficiency varies considerably among cities within the YRD. In 2014–2017, the YRD showed a more stable level of environmental efficiency, and there was an increase in the number of cities with environmental efficiency scores above 0.6 and a trend of shifting from inland to coastal cities. However, the YRD as a whole showed a marked decline of environmental efficiency in 2018, possibly due to high regional development intensity, high resource and energy consumption. (3) Within the PRD city cluster, cities with high levels of environmental efficiency are concentrated in the north and west, mainly including the prefecture-level cities of Shaoguan, Heyuan and Yunfu. This is due to the location of the eco-development zones in the northern and western regions. The main direction of development is to protect the ecological environment and develop tertiary industries such as tourism.

4.2.2. *Sub-item efficiency analysis*

Fig. 7 shows the average sub-item efficiency scores of the three urban agglomerations from 2014 to 2018. Overall, the three urban agglomerations have relatively small differences in labor, fixed assets, and energy consumption across cities, and the five-year efficiency scores of each urban agglomeration are high, with an average value greater than 0.9, except for the YRD urban agglomeration whose average efficiency score of total fixed assets is 0.8979. The YRD and PRD urban agglomerations lag slightly behind the BTH urban agglomeration in terms of the environmental efficiency scores of urban employment workers, with a difference of 0.0182 and 0.0241 respectively, while the average environmental efficiency score of each city's GDP in the three major urban agglomerations is close to 1. As for output, the three major urban agglomerations' average GDP scores are all greater than 0.97 over the five years, with the highest score of 0.9849 for the PRD urban agglomeration. The BTH urban agglomeration is behind the other two urban



	Labor	Fixed Assets	Energy Consumption	GDP	SO2	Waste Water Discharged	PM2.5	Industrial Smoke and Dust Emissions
YRD	0.9565	0.8979	0.9802	0.9764	0.7242	0.8953	0.6295	0.6088
BTH	0.9746	0.9245	0.9538	0.9784	0.8358	0.8289	0.8379	0.7440
PRD	0.9506	0.9165	0.9507	0.9849	0.7101	0.8779	0.6451	0.5408

Fig. 7. Average scores of sub-item efficiency of the three city clusters in 2014–2018.

agglomerations in terms of industrial wastewater, but the difference is relatively small. The BTH urban agglomeration also has the highest efficiency scores in the three indicators of industrial SO_2 emissions, average annual concentration of $PM_{2.5}$, and industrial smoke and dust emissions, and is significantly ahead of the YRD and PRD urban agglomerations. The efficiency scores of industrial SO_2 emissions in YRD and PRD are lower than that of BTH by 0.1116 and 0.1257, respectively. The gap in their average $PM_{2.5}$ scores is small, but there is a significant difference with BTH, whose efficiency scores are 0.8379, 1.33 and 1.30 times higher than that of YRD's and PRD's efficiency scores, respectively. Additionally, the environmental efficiency scores for industrial fume and dust emissions vary greatly in the three major urban agglomerations. In conclusion, the BTH scores best in all four indicators, which is consistent with the results of the total efficiency analysis, which may be the main factor influencing the evaluation of urban environmental efficiency.

Fig. 8(a–c) are radar plots of five input-output indicators, including GDP, industrial SO_2 emissions, industrial wastewater, average annual concentration of $PM_{2.5}$ and industrial smoke and dust emissions, for each of the three major urban agglomerations.

Among the three major urban agglomerations, the GDP indicator score of each city is the most stable, particularly the YRD urban agglomeration having the best performance, with 50% of provinces and cities reaching a GDP efficiency score of 1. Industrial wastewater is the second most stable. The overall efficiency level of the YRD city cluster is high, with eight provinces and cities achieving an efficiency score of 1, and 87.5% of the provincial and municipal regions scoring above 0.85. However, there is a large gap in the efficiency levels between the two cities of Luan and Taizhou and other cities within the city cluster, with their environmental efficiency values below 0.6. The proportion of provinces and cities' efficiency value reaching 1 in the BTH and PRD city clusters is 15.4% and 20.0%, respectively, or lower than the 25% in YRD, but there are no cities with efficiency values below 0.6 in either city cluster. The compliance of the lower efficiency value segment is better than that in the YRD urban agglomerations.

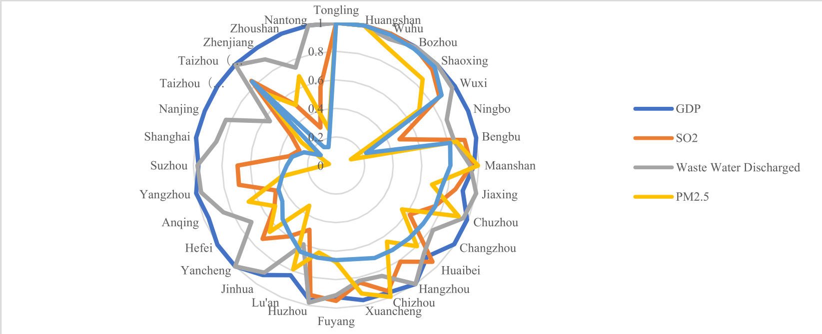
The overall situation of $PM_{2.5}$, industrial SO_2 emissions, and industrial smoke and dust emissions is less optimistic.

Only 14 provinces and cities in YRD have an annual average concentration of 0.7, accounting for less than 50% of the region, and the efficiency values of Nanjing, Suzhou and Shanghai are lower than 0.1, with the lowest value of Shanghai being only 0.05. Nanjing scores the lowest in industrial SO_2 emissions, while Shanghai scores only 0.33. Only the two cities of Tongling and Huangshan have an industrial smoke and dust emission efficiency value of 1, whereas the lowest value is 0.13 for Taizhou. Apart from this, Nanjing, Shanghai and Suzhou ranked 25, 26, and 27, respectively, and are all among the China's Top 100 Industrial Counties (Cities) in 2018. The data show that some of the more economically developed cities have good scores for urban GDP indicators, but the environmental indicators are in poor condition. Therefore, it is of great importance to pay attention to environmental protection and governance while developing a city's economy.

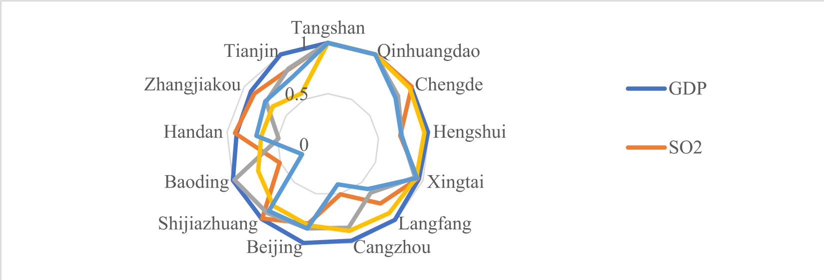
Only four provinces and cities in the BTH city cluster have efficiency scores of concentrations lower than 0.8, but all provinces and cities' data are greater than 0.5. Tangshan, Qinhuangdao, and Chengde have an industrial SO_2 emission efficiency score of 1, and Baoding and Cangzhou have an efficiency score of only 0.5, which is a large gap versus other cities. The industrial soot indicators vary widely among provinces and cities, and the radar plot fluctuates significantly. The overall score situation of the BTH city group is more concentrated, and the number of cities with lower efficiency values for each data is less than that of the YRD and PRD city groups, which is one of the factors contributing to the higher overall efficiency of the BTH city group during the five years.

The annual average concentration of $PM_{2.5}$ and industrial smoke and dust emission efficiency indicators in PRD vary greatly between provinces and cities, and only Yunfu achieves an efficiency score of 1 for $PM_{2.5}$, while the lowest efficiency score is less than 0.5 in Huizhou. All provinces and cities have an efficiency score of less than 0.9 for industrial smoke and dust emissions, with only 26.7% of the provinces and cities reaching 0.8 and the lowest efficiency score being less than 0.14 in Huizhou. Among PRD, Huizhou has many extremely unsatisfactory environmental efficiency scores, and its environmental problems are more serious in comparison with other cities. There is a large gap between cities in the environmental efficiency scores for industrial smoke and dust emissions, with the highest value of 0.98 in Yunfu and the lowest value in Huizhou whose efficiency score is only 30% that of Yunfu.

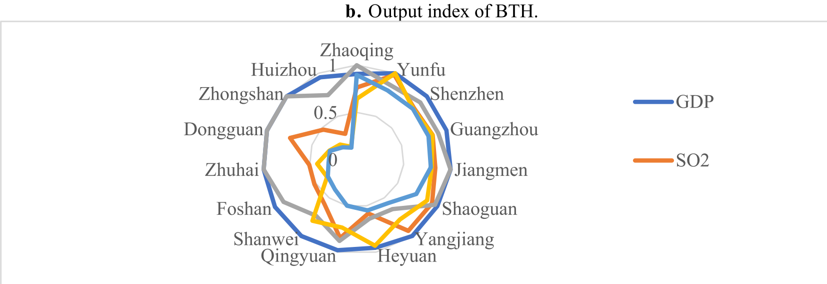
The analysis above shows that the gap in the urban agglomerations' environmental efficiency score is mainly affected by industrial smoke and dust and $PM_{2.5}$ emissions. Additionally, the average sub-efficiency scores of the three major urban agglomerations are not



a. Output index of YRD.



b. Output index of BTH.



c. Output index of PRD.

Fig. 8. a. Output index of YRD. b. Output index of BTH. c. Output index of PRD.

satisfactory and vary significantly among provinces and cities in the urban agglomerations.

These urban agglomerations should take quality improvement as the core as well as optimize and improve the total control index system of major pollutants, and meanwhile, consider limiting the initial pollutants that lead to the output of key pollutants, for example, the inclusion of Volatile Organic Compounds (VOCs), which is also one of the important precursors of secondary pollutant $PM_{2.5}$, in the total control index system will have an important role in controlling $PM_{2.5}$.

4.3. *Analysis of the spatial spillover effects*

The spatial spillover effects generated by spatial agglomeration are difficult to be addressed by traditional econometric methods, and traditional regression results are prone to erroneous research conclusions. Therefore, a spatial panel Durbin model is introduced in this paper to analyze the issue of environmental quality on the spatial evolution of urban cluster development in China. Furthermore, spatial autocorrelation, human capital, urbanization rate, and innovation are incorporated to empirically test the effect of environmental efficiency on this same spatial evolution.

4.3.1. *Variable selection*

Spatial and temporal differences in China's environmental resource endowments are clearly evident. Differences in the level of regional economic development lead to divergences in the environmental efficiency of urban agglomerations. In addition, the use of spatial measures makes allowance for better analysis of the factors affecting environmental efficiency.

All of the following have to be verified one by one: whether there is significant spatial correlation in environmental efficiency, whether there is a significant spatial spillover effect of environmental efficiency among neighboring provinces and cities, and whether GDP per capita, Foreign direct investment (FDI) agglomeration, etc. significantly affect the environmental efficiency of a region or even neighboring provinces and cities. The specific variables are selected as follows.

① Environmental efficiency is the explained variable. Environmental efficiency is improved by considering both super-efficiency and slack variables.
② A total of seven explanatory variables were selected.

GDP per capita is calculated by comparing the GDP achieved by a country during the accounting period (usually one year) with the country's resident population (or registered population) to obtain per capita GDP, which is one standard that measures the living levels of people in various countries. Unit: 10,000 yuan.

Industrialization level (Indus) refers to the total industrial output value above a certain scale. This index calculates the total value of industrial final products and labor activities expressed in monetary form by industrial legal entities with annual main business income of 20 million yuan or above during the reporting period. Unit: 100 million yuan.

FDI is a type of investment by an enterprise with a continuing interest operating in a country other than the invested country. This variable refers to the amount of capital invested in enterprises including Hong Kong, Macao, Taiwan and foreign investors. Unit: US$1 million.

Expenditures on Science and Technology (Tech) refers to one item of expenditure of the local governments, on science and technology, including science and technology management, basic research, applied research, technology research and development, science and technology condition and services, social science and technology popularization, technology exchanges and cooperation, etc. This variable is measured by the share of science expenditure within fiscal expenditure. Unit: RMB10 thousand.

Population Density (Population) is the number of people per unit of land area, which is an important indicator of population distribution of a country or region. Unit: person/km^2.

Built-up Area (Area) refers to that part in an urban administrative area that has actually been developed and constructed in patches and is basically equipped with municipal public facilities and public facilities. The scope of the built-up area generally refers the range of the actual construction land of the city can reach. Unit: km^2.

Public Transportation (Transportation) refers to the number of actual public motor (tram) vehicles operating at the end of the year. Unit: number of vehicles.

Normalized Difference Vegetation Index (NDVI), according to the spectral characteristics of the vegetation, combines the satellite visible light and near-infrared bands to form various vegetation indices. It is a simple, effective, and empirical measurement of the surface vegetation status. The data are obtained from the China Urban Statistics Yearbook and the Data Center for Resource and Environmental Sciences of the Chinese Academy of Sciences. Unit: dimensionless.

4.3.2. Spatial autocorrelation test

The spatial characteristics of the variables selected in this paper may lead to a certain degree of bias in the results measured by the fixed effects model of ordinary panel data. Therefore, in order to address bias in measurement results caused by spatial factors, this paper further constructs a spatial econometric model of panel data to test the selected samples.

Spatial correlation between environmental efficiency and the explanatory variables needs to be tested to justify the necessity of using a spatial econometric model before its analysis can be carried.

Moran's I is an index that can show the spatial correlations between variables. When Moran's $I > 0$, it indicates a positive spatial correlation, and the larger Moran's I is, the more obvious the spatial correlation is. When Moran's $I < 0$, it indicates a negative spatial correlation, and the smaller Moran's I is, the greater the spatial difference is. In addition, when Moran's $I = 0$, it shows the spatial correlation is random. The specific calculation is shown in equation (14), where n is the number of spatial samples, subscripts i and j indicate different areas, $\overline{x}$ is the average of the observed features of the spatial unit. In addition, W_{ij} represents the element on the i^{-th} row and j^{-th} column of the $n \times n$ dimensional spatial weight matrix. In this paper, the geographical distance weight matrix constructed by latitude and longitude is used as W_{ij}。

$$\text{Moran's I} = \frac{n\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(x_i - \overline{x})(x_j - \overline{x})}{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(x_i - \overline{x})^2} \tag{14}$$

Table 3 shows Moran's I for the environmental agglomeration measurement index in China from 2014 to 2018, from which the

Table 3
Moran's I value of the variables from 2014 to 2018.

Variables	2014	2015	2016	2017	2018
Environmental Efficiency	−0.066*	0.002	−0.051	−0.059	0.051**
GDP per capita	−0.015	−0.058	−0.050	−0.073**	−0.054
Indus	−0.002	−0.005	−0.006	0.001	0.008
FDI	−0.038	−0.019	−0.023	−0.025	−0.016
Tech	−0.016	−0.013	−0.044	−0.033	−0.044
Population	−0.006	−0.006	−0.009	−0.014	−0.018
Area	−0.015	−0.013	−0.018	−0.019	−0.017
Transportation	−0.011	−0.011	−0.012	−0.018	−0.016
NDVI	−0.045	−0.042	−0.040	−0.047	−0.053

agglomeration phenomenon of the country's urban agglomerations has an obvious spatial correlation. In other words, the environmental efficiency of the three city clusters in China is not completely randomly distributed.

In 2014, Moran's I is less than 0 for both environmental efficiency and each explanatory variable and shows a significantly negative correlation. Among them, the Moran indices of environmental efficiency, FDI, and NDVI oscillate at high levels, indicating that they all show high spatial autocorrelation, while Indus and Population oscillate at low levels, indicating that they show weak spatial autocorrelation. Moreover, GDP per capita shows high spatial autocorrelation from 2014 to 2018, and there is a significantly negative correlation with environmental efficiency in 2017. Moran's I for environmental efficiency shows a significantly positive correlation by 2018, and Moran's I for each of the remaining variables shows oscillations from 2014 to 2018.

From this it can be seen that traditional OLS regression estimates cannot be used, but rather a spatial econometric model should be used for analysis.

4.3.3. Measurement of spatial spillover effects

To determine whether a fixed effects or random effects model was more applicable to the analysis of the panel data in this study, the Hausman test was used. Table 4 shows the results of the Hausman test, where the original hypothesis of using a random effects model was rejected at the 5% significance level with a p-value of 0.0155, making fixed effects applicable to the spatial panel model in this study.

The LR test is further applied in order to determine whether to use area fixed, time fixed, or double fixed effects models. The results of the double fixed effect are not consistent with the comparison of area fixed and time fixed. As a result, the double fixed effect model is more appropriate.

The spatial econometric models mainly include three types: Spatial Dubin Model (SDM), Spatial Autoregressive models (SAR), and Spatial Error Model (SEM). The selection of specific models is judged by Wald and Lratio tests. The original assumptions of both the Wald test and the Lratio test are that the SDM could be degraded to SEM or SAR; if it could be degraded, then the more specific degraded model is used, if not, then the more inclusive SDM is used. Table 5 shows that both the Wald test and the Lratio test reject the original hypothesis, indicating that the SDM cannot be degraded to SEM or SAR and therefore the more inclusive SDM is used.

Table 6 is the result of environmental spillover effect under the SDM model in China from 2014 to 2018. (1) The direct effect of GDP per capita on environmental efficiency is positive (0.0340), while the spillover effect is significantly negative (−0.7693) and has the largest inhibitory effect on environmental efficiency improvement among all explanatory variables, leading to a significant negative

Table 4
Results of the Hausmann test and LR test.

Type of test	Statistic	*P*-value	Conclusion
Hausman test	17.32	0.0155**	Reject
LR test (Comparison of double fixation and area fixation)	18.32	0.2462	Accept
LR test (Comparison of double fixation and time fixation)	177.27	0.0000***	Accept

Table 5
Results of the Wald and Lratio test.

Type of test	Statistic	*P*-value	Conclusion
Wald test	17.00	0.0301**	Reject
Lratio test	17.46	0.0256**	Reject

Table 6
Results of environmental spillover effects under the SDM model.

Variable	(1) Direct effect	(2) Indirect effect	(3) Total effect
GDP per capita	0.0340	−0.7693***	−0.7352**
	(0.413)	(-2.697)	(-2.539)
Indus	−0.1425	0.0975	−0.0449
	(-1.147)	(0.111)	(-0.052)
FDI	−0.0041	−0.4827	−0.4869
	(-0.101)	(-1.539)	(-1.484)
Tech	0.5812	12.0140	12.5952
	(0.504)	(1.140)	(1.153)
Population	0.0018***	0.0093**	0.0112**
	(3.261)	(2.068)	(2.337)
Area	−0.0001	0.0091	0.0090
	(-0.244)	(1.528)	(1.477)
Transportation	−0.0001*	−0.0008**	−0.0009***
	(-1.760)	(-2.486)	(-2.601)
NDVI	0.6607	14.9201***	15.5807***
	(0.631)	(3.035)	(3.124)

Note: *, **, and *** indicate statistically significant at the 1%, 5%, and 10% levels, respectively.

total effect (−0.7352), indicating that the development of the economy in the surrounding region will have a poorer impact on the environment in the region. Inter-regional provinces and cities with good economic conditions do not necessarily have excellent environmental efficiency and there is no positive linear relationship between the two. For example, high levels of economic development will lead to slow progress in environmental efficiency at a certain point. (2) The direct effect of the level of Indus is negative but not significant, with industrial production emitting more waste products and therefore having a negative effect on environmental efficiency. (3) Both the direct and indirect effects of FDI show a negative correlation and have a suppressive effect on improving regional environmental efficiency, but this suppressive effect is not significant, probably due to the fact that regions have lower environmental access thresholds for foreign investment, which is not conducive to the improvement of environmental efficiency. (4) Both the direct and indirect effects of Tech are positive, and the coefficient of effect of indirect effect is the second highest (12.0140) but not significant, indicating that the improvement of technology level can improve regional environmental efficiency, such as better environmental protection technology, high efficiency technology research and development, etc. At the same time the sharing of advanced technology between regions still needs to be strengthened. (5) The direct and indirect effects of population show a significant positive effect at different levels, indicating that this has a significant impact on the quality and evolution of regional development and the improvement and maintenance of regional environmental efficiency, given the close inter-regional links between the population of the region and neighboring areas. (6) Area reflects to some extent the level of urbanization of the region, and since some areas have increased their level of urbanization at the expense of the environment, a higher level of urbanization of the region will have a slight inhibiting effect on environmental efficiency. (7) Transport has a significant negative impact on environmental efficiency in terms of both direct effects and spatial spillover effects, which indicates that transport has a high mobility between regions and that noise pollution, air pollution, waste oil pollution and traffic congestion generated by the transport itself can cause serious pollution to the regional environment, thus leading to lower environmental efficiency. (8) The total indirect effect of NDVI shows a significant positive utility effect through the significance test. Therefore, vegetation has a substantial effect on the inter-regional ecological environment, mainly positively influencing the development quality and spatial evolution of neighboring regions.

5. Conclusion and recommendation

5.1. Discussion

(1) We find that the environmental efficiency of cities varies considerably, as evidenced by the concentration of cities with high environmental efficiency and, correspondingly, low environmental efficiency. Feng et al. [26] argued that urban air pollution is affected not only by local environmental regulations, but also by regulations implemented in surrounding cities. In the process of studying the water quality of the Han River, Chang [22] proposed that there is an inevitable non-independence of tributary data, which is consistent with the research results of this present paper.

(2) The results obtained from the Meta-frontier DEA model analysis in this paper found that regions with higher levels of economic development were instead less environmentally efficient, for example, Nanjing, Shanghai, Suzhou and other cities in the YRD had almost the bottom environmental efficiency scores within the urban agglomerations, despite their obvious advantages in terms of economic development within the urban agglomerations and even nationwide. For the total efficiency score, Shanghai is evaluated at less than 0.3, and the average environmental efficiency score for Shanghai is only 0.2300, with a minimum value of 0.1837. This is contrary to Zhong et al. [41] conclusion that economically developed regions have an advantage in terms of environmental efficiency. This is due to the fact that these regions have pursued economic benefits at the expense of the environment. In the short term the economic benefits are achieved, raising fiscal revenues and raising the income levels of the people. However, in the long term, the benefits do not outweigh the losses. Using environmental protection to promote economic restructuring has become an inevitable trend in economic development. To protect the environment is to protect productivity, and to improve the environment is to develop productivity. It is necessary to improve the environment by upgrading environmental technology.

(3) Economic output and environmental pollution emissions are adopted as the main direction for indicator selection in this paper and the environmental indicators focus on water pollution and air pollution. We find that the gap in environmental efficiency scores for urban agglomerations is mainly influenced by industrial soot and $PM_{2.5}$ emissions, which is consistent with Cui et al. [39]. Pollution factors can be considered more comprehensively in the evaluation of environmental efficiency - for example, consider limiting the initial pollutants that lead to the emission of key pollutants, such as VOCs, which are also one of the important precursors of the secondary pollutant $PM_{2.5}$, which will play an important role in the total control target system.

5.2. Conclusion

The Meta-frontier DEA model is used in this study to conduct a quality assessment and spatial spillover effects analysis on the environmental efficiency of 60 cities in the BTH, YRD, and PRD city clusters in China from 2014 to 2018. We present the conclusion as follows.

(1) In terms of the overall development trend of urban agglomerations, the environmental efficiency values of BTH, YRD, and PRD urban agglomerations exhibit a wave-like development before leveling off from 2014 to 2018. The trend declined first and then increased during 2014–2016, illustrating a V-shape. From 2016 to 2018, the environmental efficiency values of BTH and PRD

both decreased first and then increased, while YRD's decreased year by year, and the overall efficiency of urban agglomerations declined year by year as well, mainly related to the decline in environmental efficiency of the YRD urban agglomeration.

(2) From the total efficiency scores, BTH outperforms YRD, which is better than PRD from 2014 to 2016. In 2017, YRD slightly surpassed the BTH, and in 2018 YRD continued to fall in environmental efficiency, with PRD rebounding to take first place. Analysis of the sub-item efficiency shows that YRD's $PM_{2.5}$ and industrial smoke and dust scores vary greatly among cities, with some cities approaching 0.1, which may be the main factor contributing to YRD's fall in environmental efficiency ranking.

(3) From the perspective of the efficiency score of each index, industrial wastewater is the best in environmental output, followed by industrial SO_2, while YRD, BTH and PRD all score poorly on $PM_{2.5}$ and industrial smoke and dust, whose average scores of the five years are less than 0.85. Moreover, the scores of the three major urban agglomerations vary greatly.

(4) In terms of spatial spillover effects, different indicators show various characteristics at different stages of development in the regions. Population and Transportation in a region and its neighboring regions have a significant impact on the quality and evolution of regional development. Population and NDVI have a positive effect on environmental efficiency, while GDP per capita and Transportation have a more negative effect on regional environmental optimization. The four indicators of Indus, FDI, Tech, and Area do not show significantly positive or negative effects on environmental efficiency.

5.3. Recommendation

The impact of the environmental quality of China's three major urban agglomerations on the spatial evolution of regional development is influenced by the clustering effect. As a result, each urban agglomeration should adapt to local conditions, formulate and implement strategies and countermeasures that are in line with its regional characteristics and needs, take advantage of its location and use spatial radiation to promote economic development and optimize environmental benefits.

(1) BTH urban agglomeration

The regional governments should give full play to Beijing's radiation leading role, promote the development of world-class city clusters with the country's capital as their core, highlight coordinated regional development, and pay attention to the overall development of this region. For another thing, both the direct and indirect effects of technology are positive, indicating that an increase in the level of technology can improve regional environmental efficiency. It is possible to build a green technology innovation system, strengthen the research and development of core technologies such as clean production and resource recycling, increase efforts to tackle key common technologies for energy conservation and environmental protection, eliminate green technology barriers between regions caused by technological superiority, and give full play to the spatial spillover and radiation effects of technological innovation on environmental efficiency improvement.

(2) YRD urban agglomeration

The YRD is extensive, involving many provinces and municipalities, and has a strong urban radiation capacity, with relatively small differences in development between cities, but large differences in environmental efficiency levels between cities. The spillover effect of GDP per capita is significantly negative (-0.7693) indicating that the development of the economy in the surrounding region will have a poorer impact on the environment in the region. Nanjing, Suzhou, and Shanghai, in particular, have high economic output in the data analysis, but score extremely poorly on some environmental indicators. Therefore, it is feasible to prioritize the development of key areas that will further radiate and drive other regions, and ultimately achieve overall environmental efficiency improvements in urban agglomerations through coordinated development between cities.

(3) PRD urban agglomeration

In the PRD urban agglomeration, the concentration of environmentally efficient cities in the north and west is due to the fact that the region is an ecological development area, where the main direction of development is to protect the ecological environment and develop tertiary industries such as tourism. Also, both the direct and indirect effects of NDVI are positive, to improve the environmental efficiency scores of the cities in the southern and eastern PRD, the resource consumption and environmental constraints in the urbanization process need to be fully considered. The governments in the region need to give prominence to the construction of ecological civilization, follow the concept of ecological urbanization and green development, and make use of the PRD's ecological advantages to restore it via the construction of forest parks, wetlands, and strong pollution control.

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Production notes

Author contribution statement

Fang-rong Ren: conceived and designed the experiments.
Zhe Cui: performed the experiments.
Xin-ge Guan: analyzed and interpreted the data.
Xue-rong Zhang: contributed reagents, materials, analysis tools or data.
Xuan Zhang and Zhi-ye Jing: wrote the paper.

Data availability statement

Data included in article/supplementary material/referenced in article.

Declaration of competing interest

We declare that we have no financial and personal relationships with other people or organizations that can inappropriately influence our work, there is no professional or other personal interest of any nature or kind in any product, service and company that could be construed as influencing the position presented in, or the review of, the manuscript entitled, "**Environmental Quality Assessment and Spatial Spillover Effects of Three Urban Agglomerations in China: A Meta-EBM approach**".

Appendix

In accordance with *GB 3838–2002*, based on the environmental functions and protection objectives of surface water, the surface water in China is divided into five categories [42].

Water quality classification	Water quality	Characterization of color	Functions
I-Type and II-Type water	Superior	Blue	Grade I relate to source water and national nature reserves. Grade II includes primary protection areas for centralized drinking water sources, precious fish sanctuaries, fish and shrimp spawning grounds, etc.
III-Type	Good	Green	Grade III relates to secondary protection areas for centralized drinking water sources and general fish protection and swimming areas.
IV-Type	Mild pollution	Yellow	Grade IV applies to general industrial and recreational water areas where there is direct human contact.
V-Type	Moderate pollution	Orange	Grade V refers to agricultural water use areas and waters with general landscape requirements.
Inferior V-Type	Severe pollution	Red	Apart from adjusting to the local climate, the inferior V-Type is poorly functional.

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