



Carbon emission efficiency and spatio-temporal dynamic evolution of the cities in Beijing-Tianjin-Hebei Region, China

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Abstract

Improving carbon emission efficiency (CEE) would promote the development of the green and low-carbon economy in the Beijing-Tianjin-Hebei (BTH) region, China. This paper uses the EBM model of unexpected output to measure the city-level CEE of the BTH region from 2007 to 2016. The spatial distribution characteristics and evolution law of CEE are analyzed with respect to overall and local aspects, and the spatial quantile regression model is used to verify the influencing factors of CEE. The main findings are as follows: (1) The carbon emission in the BTH region is considered to be of medium efficiency, and there are eight cities within the region at middle- and high-efficiency levels. The overall efficiency values show a downward trend. Beijing, Cangzhou, Baoding have high-CEE values, whereas Handan, Tangshan, and Zhangjiakou have low-CEE values. (2) The CEE values for BTH show significant spatial agglomeration characteristics at both the global and local levels. The “H–H” agglomeration areas are primarily distributed in the central region, and the “L–L” agglomeration areas are chiefly distributed in the southern and northern regions. The spatial pattern change is generally stable. (3) The selected factors, URB, PGDP, DS, ISG, FDI, and TEL, have different regression coefficients on CEE at different quantiles.

Keywords Beijing-Tianjin-Hebei cooperation · Carbon emission efficiency · Super-efficiency EBM model · Spatio-temporal effect · Spatial quantile regression

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1 Introduction

Within the context of the global response to the challenge of climate change, as the largest developing country in the world, and with the highest global carbon dioxide emissions, China is facing the dual pressure of economic development and carbon emission reduction. The Beijing-Tianjin-Hebei (BTH) region, an important player in the country's regional economic layout, plays a vital role in driving China's economic development. Since the 'Planning Outline of Collaborative Development of Beijing, Tianjin and Hebei Provinces'¹ was proposed by the Chinese government in 2015, the integration of the BTH region has formally become a national strategy, and BTH regional cooperation has shown remarkable results in reducing emissions. The key tasks of strengthening the environmental protection of the BTH region and bolstering the joint prevention and control of regional pollution were again proposed at the Beijing-Tianjin-Hebei Cooperative Development Forum in July 2018. This provides a strong indication that the energy consumption structure and carbon emissions of the BTH region need to be further improved.

In 2018, the total GDP of the BTH region was 7.9 trillion yuan (or 8.6% of the country's total GDP²) and represented an increase of 18.8% compared to 2014 when the BTH integration strategy was first proposed. However, the contradictions between economic development and the demands of the resource environment are also more prominent in the BTH region. For example, the energy consumption in 2017 was 0.62 billion tons of coal equivalent (tce), accounting for about 8.9% of China's total energy consumption.³ This indicates that the region's economic growth is still accompanied by high levels of energy consumption and emissions. To solve this problem, some scholars believe that scientifically improving the levels of CEE would provide a direct and effective method through which to achieve a reduction in carbon emissions and an increase sustainable development (Amini et al., 2018).

The concept of carbon emission efficiency (CEE) has received extensive attention in the research on carbon emissions and emission reduction policies with respect to taking economic and social development, as well as environmental protection into account and the implementation of green sustainable development. No clear definition of CEE has yet been put forth. However, through examining and summarizing the existing literature, CEE can be defined as the causal transformation efficiency between the relevant factors that affect carbon emissions (i.e., the level of technological development, capital, personnel input, etc.) and carbon emissions (Ang, 1999; Kaya & Yokobori, 1999; Mielnik & Goldemberg, 1999). It can reflect the economic development model of a region and the degree of efforts made to combat climate change (Sun, 2005). CEE estimation methods under a single factor, such as Carbonization Index (Fernández González et al., 2015; Mielnik & Goldemberg, 1999) and Carbon Intensity (Acheampong & Boateng, 2019), can only measure CEE from a certain aspect. In contrast, total factor efficiency evaluation has the advantage of being able to determine the production frontier, and the evaluation results will be more comprehensive and holistic (Cheng et al., 2018). Therefore, total factor CEE will be evaluated in this study.

¹ BLRQHD (The Bureau of Land and Resources Qinhuangdao). Collaborative Development of Beijing, Tianjin, and Hebei Province. The Bureau of Land and Resources Qinhuangdao; 2015. <http://www.hebqhdsqt.gov.cn/gtzyj/front/6048.htm>.

² NBS. China Statistical Yearbook 2019. Beijing: China Statistics Press; 2019.

³ NBS. China Energy Statistical Yearbook 2018. Beijing: China Statistics Press; 2018.

The research on CEE has made great progress in recent years, especially with respect to the situation in China. The research objects cover many regions and various industries, mainly including industries in different provinces (Cheng et al., 2018; Wang et al., 2019a), 30 provinces and province-level municipalities (Ding et al., 2019; Liu et al., 2016; Meng et al., 2016; Wang et al., 2016), manufacturing (Li and Cheng 2020), urban (Liu et al., 2018a), airlines (Wang et al., 2015), the thermal power industry (Yan et al., 2017), and the construction industry (Zhou et al., 2019), etc. As for research on city level, some scholars have conducted energy conservation and emission reduction assessments on more than 200 cities in China (Wang et al., 2015; Zhou et al., 2016), and recently Zhou et al. (2020) have carried out research on urban green development efficiency (UGDE) in 285 prefecture-level cities in China (Zhou et al., 2020). The research content primarily involves the measurement of carbon emissions (Meng et al., 2016; Wang et al., 2012, 2016), forecasting (Chen et al., 2020), and the analysis of influencing factors (Sun & Huang, 2020; Tan et al., 2020). Table 1 indicates the specific research information on CEE.

According to the existing literature, the methods for measuring the total factor CEE mainly include the following two, stochastic frontier analysis (SFA) (Sun & Huang, 2020) and data envelopment analysis (DEA) (Meng et al., 2016). Considering the frontier boundary obtained from SFA is random and requires the explanatory variables to be independent of each other, while DEA can evaluate multiple input–output indicators at the same time without previous acquaintance of the correlation between indicators (Molinos-Senante et al., 2016). So the DEA model is selected for CEE estimation in this study. As a superior evaluation method, DEA method has been widely used in efficiency evaluation and ranking, involving the performance measurement in many occasions or fields, such as energy (Wu et al., 2012; Yang et al., 2018), economy (Shuai & Fan, 2020; Wu et al., 2020), environment (Cecchini et al., 2018), production (Wu et al., 2019). The results of quantitative analysis have practical significance for guiding environmental policy, energy policy, and economic planning. Recently, Meng et al. focused on ranking information based on data envelopment analysis model and believed that a better understanding of grade reversal phenomenon has an important enlightenment for energy efficiency assessment and policy making using DEA (Meng et al., 2019).

In recent years, the theoretical basis and model of DEA are constantly improved and developed, as summarized by Zhou et al. (Zhou et al., 2016) and Meng et al. (Meng et al., 2016). In terms of theory and model construction, most of the traditional DEA models belong to the measurement of radial and angle, without consideration of slack variables in the objective function, so that the input–output ratio does not match the actual production state. Based on the traditional radial DEA model, Tone proposes an SBM model that can relax input and output to calculate efficiency (Tone, 2001). It is a non-radial, non-angled model, and the adjustment of inputs and outputs can be disproportionate (Wang et al., 2019a). However, most coal efficiency measures based on radial or non-radial methods are found to expand or underestimate the efficiency improvement (Tone & Tsutsui, 2010; Wu et al., 2019). To this end, Tone further proposed a mixed distance function EBM model that takes into account both radial and non-radial characteristics, which can more accurately and comprehensively calculate the efficiency values (Tone, 2010). Based on the following two considerations, this paper decided to refer to the EBM model to estimate carbon efficiency. On the one hand, EBM model is widely used to estimate the efficiency in different fields (Wu et al., 2019, 2020; Yang et al., 2018), but relatively few in carbon emission. On the other hand, in the research of CEE, most of the DEA methods are based on the traditional radial or non-radial models (Choi et al., 2012; Iftikhar et al., 2016), which reflects the deficiency of methodology.

Table 1 Research on carbon emission efficiency

Paper	Research object	Research content	Methods
Cheng et al. (2018)	China's provincial industrial sector	Estimates CEE and analyzes dynamic evolution	NDDF
Wang et al. (2019a)	China's industries	Estimates and decomposes CEE and dynamic changes	TCFM
Liu et al. (2016)	30 regions in China	Analyzes CEE and differences between regions	SBM
Ding et al. (2019)	China's 30 provinces	Evaluates CEE and examines dynamic changes	CE-MPI
Wang et al. (2016)	China's 30 provinces	Evaluates CEE and reduction costs	NDDF
Li et al. (2020)	China's 31 manufacturing industries	Measures CEE and analyzes its root causes	NDDF
Liu et al. (2018a)	China's cities	Evaluates and decomposes CEE	GDEA
Wang et al. (2020)	13 Chinese airlines	Estimates static and dynamic CEE	GSBM; GML
Yan et al. (2017)	China's power industry	Evaluates CEE	Undesirable SBM
Zhou et al. (2019)	China's construction industry	Measures CEE, its interior driving factors and cross-industrial shock effects	Super-SBM DEA
Sun and Huang (2020)	China's 30 provinces	Evaluates CEE and explores the impact of urbanization	SFA
Tan et al. (2020)	China	Estimates CEE and its policy and economic drivers	FSFA
Wang et al. (2019)	China's provinces	Estimates CEE and spatial Moran's and LISA cluster	DDF
Meng (2019)	China's 29 regions	Estimates CEE	DDF
Sun et al. (2019)	60 countries	Evaluates CEE and the impact of the position of manufacturing	GVC
Wang et al. (2019b)	China's provinces	Estimates CEE and abatement potential	SBM
Liu et al. (2018b)	10 typical urban agglomerations	Analyzes CEE and the effects of urbanization	IPCE
Li et al. (2018)	Yangtze River Delta, China	Examines the effects of urbanization on CEE	DEA; SLPTM

The meaning of abbreviations in "Method" column is as follows: NDDF means Non-radial Directional Distance Function; SBM means Slacks-Based Measure; CE-MPI means Cross Efficiency-Malmquist Productivity Index; GDEA means Global Data Envelopment Analysis; DDF means Directional Distance Function; GVC means Global Value Chain; SFA means Stochastic Frontier Analysis; FSFA means fixed-effect stochastic frontier approach; DDF means Direction Distance Function; SBM means Slacks-Based Measure; TCFM means Three-level Common Frontier Model; GSBM means Global Slack-Based Measure; GML means Global Malmquist-Luenberger Productivity Index; SLPTM means Spatial Lag Panel Tobit Model; IPCE means Ideal Point Cross Efficiency.

In a study of spatio-temporal effects, Tobler's first theorem of geography shows that everything between regions is connected (Gale, 1979). The research on spatio-temporal effects covers many fields including water resources, climate, and energy and characterizes their geographical interactions (Welder et al., 2019; Xu et al., 2019). Recently, Yu et al. (2021) have carried out research on the spatiotemporal patterns and urban facilities determining cycling activities in the downtown area of Beijing, which provides an effective reference for this article to explore the spatio-temporal effects and influencing factors of smaller regional units (Yu et al., 2021). However, relatively few studies combine CEE and its influencing factors with time-space effects (Wang et al., 2019). Since Spatial Econometrics proposed by Anselin (Anselin, 1988) and Lesage (Lesage, 2008) systematically, it has been applied to the field of environmental economy including carbon emission with its irreplaceable advantage of considering spatial effects. However, it is still relatively scarce on CEE influencing factors. In addition, the general spatial measurement model's analysis of influencing factors is based on the mean regression of OLS. When the data distribution shows the characteristics of thick tail, the accuracy of the mean regression result is low (Zietz et al., 2008). Quantile regression can regress different quantile points separately and propose more information. Therefore, this study combines quantile regression with spatial measurement model as spatial quantile regression model to study the influencing factors of CEE.

To summarize, the existing research has achieved some results in the study of measurement, spatio-temporal effects, and influencing factors of CEE, but the research contents are independent of each other and do not form a complete research system. Besides, relatively few studies have yet been conducted on carbon emission-related issues in the BTH region. Therefore, this study takes 13 cities in BTH region as the research object, including two municipalities and 11 prefecture-level cities, and 2007–2016 as the research period, comprehensively considering the timeliness and availability of individual indicator data. The CEE on a city level is estimated applying super-efficient EBM model. Then the spatio-temporal dynamic evolution analysis is carried out by using spatial autocorrelation index, taking account of the spatial interaction effect between cities. Besides, the combination of quantile regression and spatial measurement model is used to analyze the influencing factors of CEE. And some implications and suggestions are proposed to the policy makers based on the results and analysis above.

The main contributions and innovations of this article are as follows. First, this study compensates for and perfects the research on carbon emissions in the BTH region from the perspective of research objects and methodology. Taking cities as the smallest research unit can propose more specific and feasible emission reduction strategies. Second, the analysis of spatio-temporal characteristics can reflect the spatial interaction effects of CEE, for it can consider the exchange and flow of resources and people between cities. And the exploration of influencing factors of CEE takes both spatial effects and quantile regression into consideration, which can provide a more accurate and diversified information. Finally, this study integrates the two major research contents of CEE, taking the spatio-temporal effects of CEE and its influencing factors into a closed loop, so as to form a complete research system of CEE in BTH region, which can provide references for related research in other regions or countries.

2 Methodology and data

2.1 Non-radial EBM super-efficiency model

The super-efficiency EBM model used in this paper is an improved efficiency value measurement model based on the traditional SBM model. Traditional DEA models, such as representative CCR (Ang, 1999) and BCC (Liu et al., 2018a), mainly use a radial distance function. They improve the invalid DMU by increasing (reducing) all inputs (outputs) in the same proportion and ignore the slack variables so that the efficiency values are inaccurate. The non-radial SBM model based on slack variables proposed by Tone (Molinos-Senante et al., 2016) has improved the accuracy of efficiency measurement and becomes one of the main methods for carbon efficiency measurement (Li & Cheng, 2020; Meng et al., 2016; Wang et al., 2016). The non-radial model peels off the influence of input–output slack part in order to obtain the maximum input reduction rate, but this is at the cost of the possibility that different proportions of the original input resources will be discarded.

In addition, the traditional SBM was found embarrassing situation that there are many effective DMUs of 1 in efficiency measure, which restricts distinction and ranking of DMUs. To the blemish of the traditional DEA models that can only distinguish inefficient decision-making units but not efficient decision-making units, Andersen and Petersen (Wang et al., 2020) proposed the super-efficiency model of data envelopment analysis. The efficiency value calculated by the super-efficiency EBM can exceed 1, a function that greatly reduces the possibility of multiple regions showing the same efficiency levels, and which meets the needs of all DMU evaluation and ranking so that this model's rationality and applicability are greatly enhanced. Meng et al. (Meng et al., 2019) used five different DEA models to study the impact of rank reversal on regional energy efficiency evaluation. The results indicated that SBM shows the smallest rank reversal when measuring the energy efficiency of 30 provinces in China. Less rank reversal means the efficiency evaluation is more robust. Theoretically, the ideal DEA ranking model shall keep the ranks of other DMUs from changing after the addition or removal of one or more DMUs (Liu et al., 2016). It is found that the efficiency evaluation results based on SBM model can provide more stable guidance and suggestions for us to improve CEE. Wu (Fernández González et al., 2015) put forward a super-PEBM model based on Pearson correlation coefficient on the basis of EBM model and super-efficiency model on the research of green economy efficiency (GEE) and used the panel data of China from 2008 to 2017 to compare the results of CCR, SBM, and EBM models on GEE. The results indicated that there are relative advantages of EBM from the perspective of the model, and it is proved that the results of SBM, EBM, and PEBM are consistent by Pearson correlation analysis and paired sample t-test. As mentioned above, EBM model has the advantages of both radial proportion improvement and non-radial relaxation improvement, making it an advanced means to estimated efficiency. This paper uses this model to estimate the CEE of BTH region on a city level.

The expressions and constraints are shown in Eqs. (1) and (2), respectively.

$$\min \frac{\theta - \varepsilon^- (1 / \sum_{i=1}^m \omega_i^-) \sum_{i=1}^m \frac{\omega_i^- s_i^-}{x_k}}{\varphi + \varepsilon^+ (1 / \sum_{r=1}^q \omega_r^+) \sum_{r=1}^q \frac{\omega_r^+ s_r^+}{y_k}} \tag{1}$$

Constraints are:

$$\text{s.t.} \begin{cases} X\lambda - \theta x_k + s_i^- = 0 \\ Y\lambda - \varphi y_k - s_i^+ = 0 \\ \lambda s_i^- \geq 0, \theta \leq 1, \varphi \geq 1 \end{cases} \tag{2}$$

where λ is the linear combination coefficient of the decision unit DMU, m and q are the number of input indicators and output indicators, s^- and s^+ are the relaxation variables of input and output, θ is the radial efficiency value calculated by the CCR model, ω is the relative weight of each input index and satisfies $\sum \omega = 1$. ε is one of the key parameters and the value range is $[0,1]$, which indicates the importance of the non-radial part in the calculation of the efficiency value: When $\varepsilon = 0$, the EBM model will be simplified to a radial CCR model; when $\theta = \varepsilon = 1$, the EBM model will be transformed into the SBM model.

2.2 Spatial autocorrelation index

In the past 20 years, improvements in geographic information systems and computer technology have led to the rapid expansion of statistical methods for spatial data analysis (Zhang, 2016). Spatial autocorrelation analysis is a spatial data analysis technique that is widely used in economic and social regional research (Ma & Chen, 2019), and it is divided into the two aspects of global autocorrelation analysis and local autocorrelation analysis (Li, 2015; Talen & Lee, 2016). The former is used to evaluate whether there is a spatial autocorrelation overall, and it is measured by the global Moran’s I value. Its essence is a standardized spatial covariance. The latter is used to evaluate local spatial differentiation patterns. It is measured by the local Moran’s I value, which is called the Local Indicator of Spatial Association (LISA). It is based on the analysis of the global Moran’s I, which can accurately evaluate the global spatial heterogeneity. By evaluating the correlation of parameters between spatially similar or adjacent regions, the Moran’s I quantifies the spatial aggregation and connectivity between clusters (Thompson & Declercq, 2018). The expression is seen in Eq. (3) below:

$$I = \frac{\sum_{i=1}^n \sum_{j \neq i}^n w_{ij} \ominus x_i - \bar{x} \ominus \ominus x_j - \bar{x} \ominus}{\sigma^2 \sum_{i=1}^n \sum_{j \neq i}^n w_{ij}} \tag{3}$$

where x_i is the observed value of area i , and n is the number of observed values, $\bar{x} = \frac{1}{n} \sum_{i=1}^n x_i$, $\theta^2 = \frac{1}{n} \sum_{i=1}^n (x_i - \bar{x})^2$, $\theta^2 = \frac{1}{n} \sum_{i=1}^n (x_i - \bar{x})^2$. The spatial weight matrix w_{ij} is a binary adjoint matrix. Equation (4) is the Z test statistic.

$$Z = \frac{I - E(I)}{\sqrt{Var(I)}} \tag{4}$$

where $E(I)$ is the expectation, and $Var(I)$ is the variance. If I is significantly positive, it indicates that there is a positive spatial correlation, and the regions with high (low) CEE values are spatially concentrated. Global space autocorrelation assumes that the space is homogeneous and cannot reflect the characteristics of local agglomeration. Local space autocorrelation analysis is required. The local spatial autocorrelation reflects the degree of spatial correlation between each city and adjacent cities. The local Moran's I formula is seen in Eq. (5):

$$I_i = z_i \sum_{i \neq j}^n w_{ij} z_j \quad (5)$$

where I_i is the local Moran's I of area I , z_i is the standardized Z of the CEE value of area I , and w_{ij} is the spatial weight matrix. Where the local Moran's I is positive (negative) it indicates that the elements of similar (different) type attribute values are close to each other, and larger absolute values indicate higher proximity. The Moran scatter plot is a scatter plot with the observed value Z as the abscissa and the corresponding spatial lag factor W_z as the ordinate. There are four types of aggregation: High-High (H-H) aggregation, Low-Low (L-L) aggregation, Low-High (L-H) aggregation, and High-Low (H-L) aggregation.

2.3 Spatial quantile regression model

Quantile regression model is an improved model based on traditional OLS regression. The OLS regression that reflects the mean regression alone is convenient for explaining many phenomena in the traditional sense. However, when the distribution of the sample statistics of the research object has the characteristics of sharp peaks or thick tails, the least squares method that reflects the mean regression alone will no longer have the above advantages, and even smooth out or lose a lot of key information. In order to make up for the shortcomings of this regression method, Koenker and Bassett proposed the idea of quantile regression in 1978 (Koenker & Bassett, 1978). Conditional quantile estimation on different quantiles of the dependent variable can describe the overall regression of the independent variable to the dependent variable or focus on the regression of a specific quantile. Compared with OLS regression, quantile regression analysis can provide richer information and avoid many arbitrary and fallacious conclusions. It is of great significance to the study of complex economic and social activities. The basic form of the quantile regression model is as follows.

$$Q_y(\tau|x) = a_0 + a_1x_1 + a_2x_2 + \dots + a_kx_k + Q_u(\tau) \quad (6)$$

where τ is the quantile set artificially, and the most common quantile settings are 10%, 25%, 50%, 75%, and 90%. Generally, 10% quantile regression is used to reflect the tail regression near the minimum value of the dependent variable, and 90% quantile regression is used to reflect the tail regression near the maximum value of the dependent variable. The 50% quantile regression is theoretically the general mean regression.

Spatial quantile regression is essentially a combination of spatial econometrics theory and quantile regression thinking, and its appearance is not long. After Kostov (Kostov, 2009), Liao and Wang (Liao & Wang, 2010), and Zietz (Zietz et al., 2008) made early attempts to use spatial autoregressive (AR) models to estimate quantiles, scholars realized the importance of the combination of the two. This paper introduces the idea of quantile regression into the spatial measurement model, to expand the research on the influencing

factors of CEE. A spatial quantile regression model is established based on the spatial Durbin model, and its basic form is as follows.

$$y_{i,t} = \rho(\tau) \sum_{j=1}^n w_{i,j} y_{i,t} + \alpha + \beta(\tau) x_{i,t} + \varphi(\tau) \sum_{j=1}^n w_{i,j} x_{i,j,t} + \mu_i + \lambda_t + \varepsilon_{i,t} \quad (7)$$

where $y_{i,t}$ and $x_{i,t}$ represent the dependent variable and independent variable (or explanatory variable) of the spatial unit i in year t , respectively. $\sum_{j=1}^n w_{i,j} y_{i,t}$ is the spatial lag vector, describing the spatial adjacency of the observations. ρ is the spatial autocorrelation coefficient, reflecting the effect of adjacent regions on local region. α is a constant parameter, and β and φ are the fixed unknown coefficient parameter of the independent variable $x_{i,t}$. $\varepsilon_{i,t}$ is an independent and uniformly distributed error term, and μ_i and λ_t are used to describe space-specific effects and time-specific effects, respectively. τ has the same meaning as formula (6).

2.4 Index Selection

In this paper, the total GDP (actual), number of urban employees, and fixed asset inputs collected in each city area are all derived from the China City Statistical Yearbook, and the energy consumption data are sourced from the city-level statistical yearbooks at prefecture-level cities. CO₂ emissions are calculated using the carbon emission coefficient method provided by IPCC (2006). The carbon emission coefficient refers to the carbon emission generated by various energy sources during the combustion or the use of a unit of the energy (the carbon emission coefficient of this energy is generally considered to be unchanged during use). It is expressed as Eq. (8):

$$CO_2 = \sum_{i=1}^n E_i \times NCV_i \times CEF_i \times COF_i \times 44/12 \quad (8)$$

where i represents the type of fossil fuel, E_i represents the energy consumption of various fossil fuels, NCV_i is the average low calorific value of various fuels, CEF_i is the carbon emission coefficient per unit calorific value, and COF_i is the carbon oxidation factor. Fossil energy types include charcoal, coke, crude oil, gasoline, fuel oil, kerosene, diesel, and natural gas, so n is 8.

There are two types of indicators: input indicators and output indicators. The selection of indicators is shown in Table 2. When we select input indicators, we should consider the data from the three perspectives of "human input, capital input, and energy input." The number of employees, the amount of fixed asset investment, and energy consumption were selected as input indicators (fixed asset investment is based on 2006 data and calculated by the perpetual inventory method). When we select output indicators, we should choose these according to two perspectives: expected output and undesired output. The expected output index is the actual GDP, and the undesired output (bad output) is the CO₂ emissions. The data come from the China City Statistical Yearbook and the statistical yearbooks for each city.

Table 2 Measurement index system of CEE in the BTH region

Indicator type	First-level indicators	Secondary indicators
Input indicator	Manpower input	Number of employees
	Capital investment	Investment in fixed assets
	Energy input	Energy consumption
Output indicator	Expected output	Real GDP
	Unexpected output	CO ₂ emissions

3 Results and discussion

3.1 Spatial–temporal analysis of CEE

3.1.1 Results and analysis of CEE in the BTH region

Based on the results of the super-efficiency EBM model that were conducted by MAXDEA software, this study estimated CEE of 13 cities in BTH region in 2007–2016. Feng and Li (2017) have measured CEE of 13 cities in BTH region during 2005–2014, using SBM model with undesired output (Feng & Li, 2017). In order to visually show that the EBM estimation results are better, the CEE estimations of EBM are compared with SBM from Feng and Li (2017), which are shown as radar charts in Fig. 1. Considering that the overlap research year of the two research, the comparison results of 2007, 2010, and 2014 are selected for display.

It can be seen that the CEE results of undesired-output SBM and super-efficiency EBM are quite different in most cities, especially in some high-CEE cities, like Beijing, Baoding, Cangzhou, etc. The estimations of these high-CEE cities obtained from undesired-output SBM are equal to 1, while they are greater than 1 from super-efficiency EBM, indicating that the estimated efficiency value of the EBM model is not limited to 1. Besides, there are also some differences in CEE of other cities from the two kinds of DEA models, indicating that the super-efficiency EBM effectively improves the accuracy of the estimation compared with undesired-output SBM.

The CEE calculated by the super-efficiency EBM model reflects the overall and local efficiency levels of the BTH region during the ten years from 2007 to 2016. The estimation results are detailed in Appendix Table A1. From the magnitude and evolution of the estimated results, CEE in BTH cities has the following characteristics:

Firstly, the overall CEE value of the BTH region is generally at a moderately high level, and there are 4 low-efficiency cities, 4 medium-efficiency cities, and 5 high-efficiency cities. Besides, the average CEE of the 13 BTH cities from 2007 to 2016 is between 0.596 and 0.781, showing a downward trend in fluctuations. And the maximum variation coefficient of CEE for the BTH region is 0.21, showing that the fluctuation range is small. The overall difference does not change significantly during the period, and the overall spatial pattern is relatively stable (Fig. 2).

The evolution trend of the CEE values of the BTH cities generally shows a downward trend in fluctuations, and the partial evolution basically coincided with the overall evolution pattern. There are three types of evolution trajectories of each city-level CEE: stationary, fluctuating, and declining. The evolution results and 3 types of the cities in the BTH region from 2007 to 2016 are shown in Fig. 3.

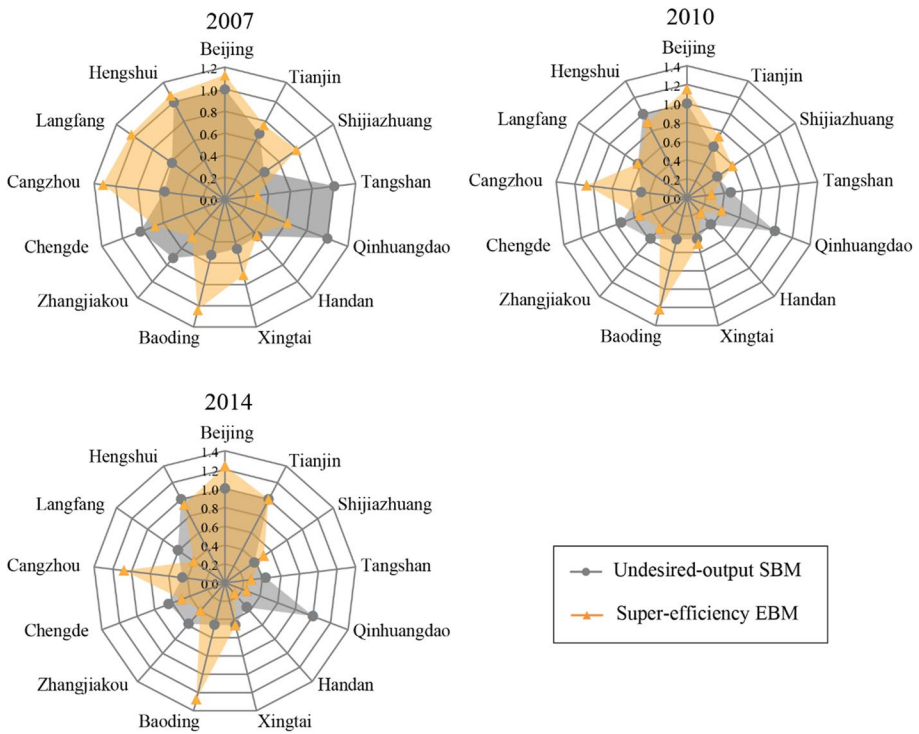


Fig. 1 Comparison of CEE estimations obtained from different DEA models

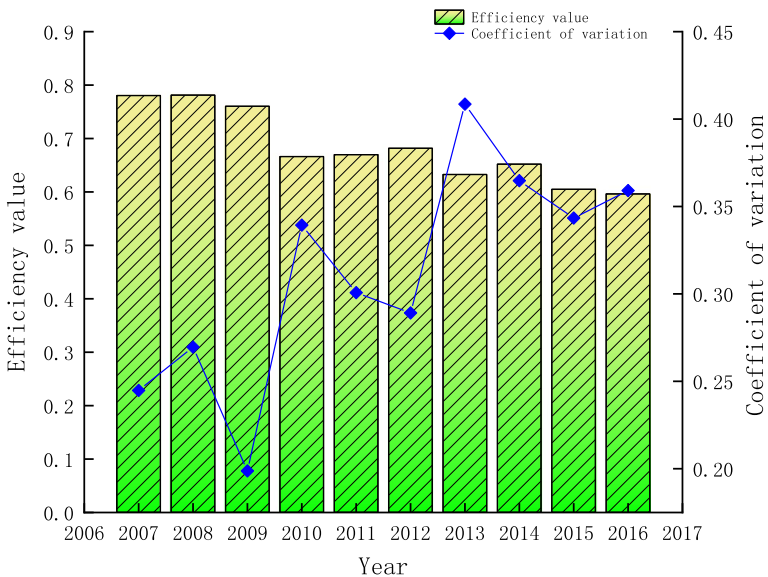


Fig. 2 CEE value and coefficient of variation for BTH region

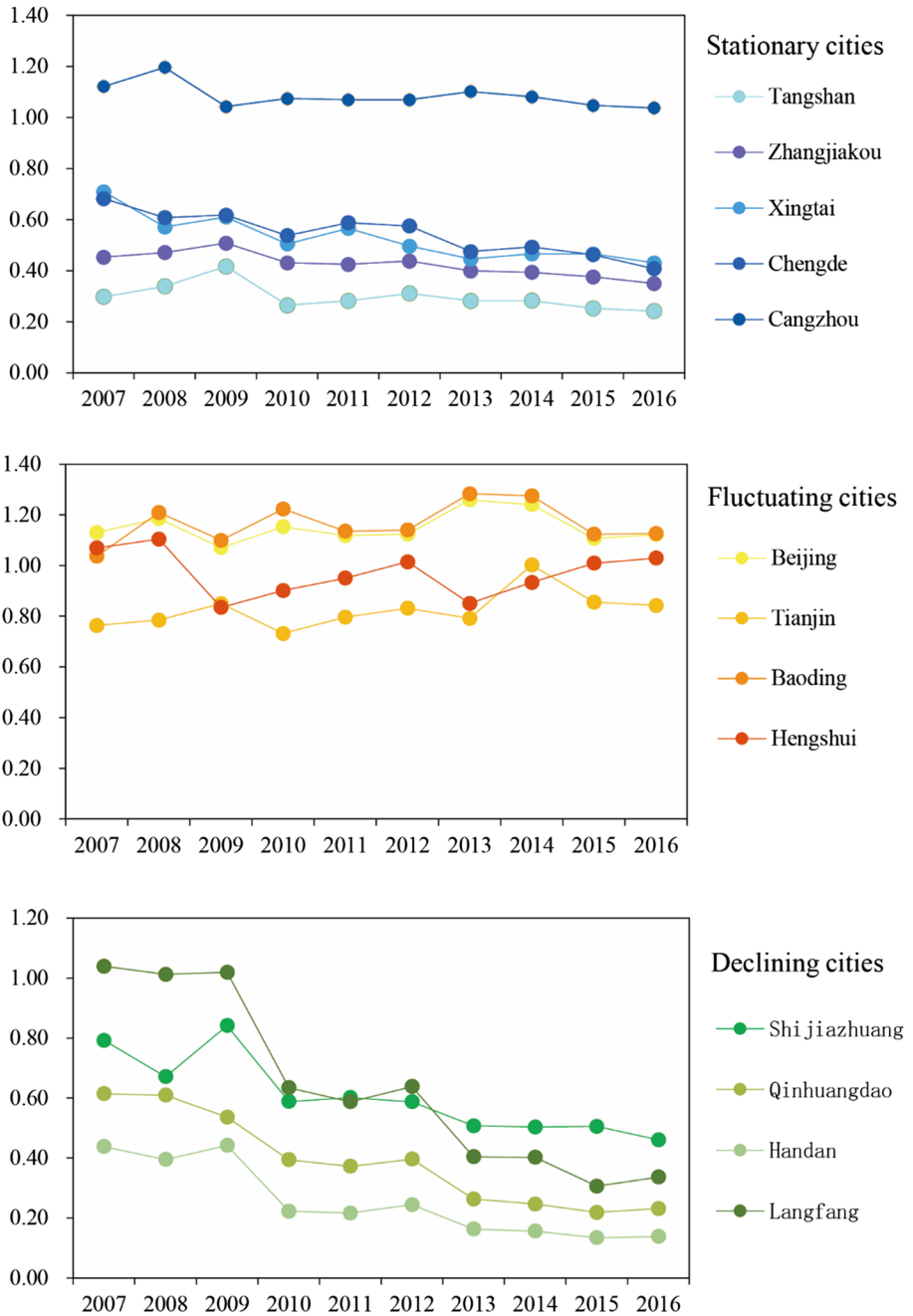


Fig. 3 Evolution results and types of CEE in BTH cities

Stationary cities include Cangzhou, Zhangjiakou, Tangshan, Chengde, and Xingtai. During the study period, the CEE estimates of these cities did not change much. It shows that the level of economic development and development structure is relatively stable. Cities such as Tangshan and Chengde that have always maintained a low level of CEE have huge emission reduction potential and should be focused on in the overall BTH emission reduction strategy. Fluctuating cities include Baoding, Beijing, Hengshui, and Tianjin; the CEE levels of these cities have remained at a relatively high level, and the large fluctuations are due to related explorations of emission reductions, with mixed results. We can extract experience from these cities' emission reduction exploration to provide guidance for other cities' emission reduction efforts. Declining cities include Langfang, Handan, Shijiazhuang, and Qinhuangdao. The carbon efficiency of these cities is decreasing year by year, and special attention should be paid to their development models to find out the reasons for the reduction in CEE. If it is a temporary development pain, it is necessary to reduce the negative impact through the joint efforts of the region as a whole. If there is a problem with the development model, it is necessary to stop the loss in time and strictly rectify it.

The local level of CEE in the BTH region is measured by the differences in CEE values for each city. The difference in the CEE value of each city represents the strength of its equilibrium. The Chinese government proposed an integrated development strategy for Beijing-Tianjin-Hebei in 2014.⁴ Considering that China's construction planning and economic development were planned for five years, and the time when the BTH integration strategy is proposed is close to the research period, the time interval was determined to be 3 years. So we show the results of four years with equal time spans, namely 2007, 2010, 2013, and 2016, while the remaining years that are not shown have little change and do not affect the overall dynamic distribution trend. Besides, this study divides the BTH region into northern region, central region, and southern region. Northern region includes Zhangjiakou, Chengde, Tangshan, and Qinhuangdao, central region includes Beijing, Baoding, Langfang, Tianjin, and Cangzhou, while southern region includes Shijiazhuang, Hengshui, Xingtai, and Handan. The distribution map of CEE in BTH region is drawn for in-depth analysis of the evolution of dynamics distribution, shown in Fig. 4.

It can be seen that there are significant differences in the CEE of the different locations. Throughout the designated study periods, the CEE of Zhangjiakou, Tangshan, and Handan is relatively low and can be regarded as low-CEE cities. In contrast, the CEE of Beijing, Baoding, Cangzhou, Tianjin, and Hengshui is relatively high and can be seen as high-CEE cities. Among them, Beijing and Baoding have the highest CEE values and have been maintained at a high level, while the CEE of Langfang, Shijiazhuang, and Xingtai decreased significantly after 2010 and gradually evolved into low-CEE cities. BTH's CEE exists spatial agglomeration within this region. The CEE values in the central of the BTH region are significantly higher than those in the north and south region, showing spatial agglomeration characteristics centered on Beijing. The efficiency values of the northern part of the BTH region have shown low values throughout the years under study, while the southern region has shifted from higher levels to lower ones. After General Secretary Jinping Xi put forward the concept of BTH integration in 2014, the Beijing, Tianjin, Baoding, and Langfang were designated as core functional areas, but their performance in CEE is quite different. With respect to these cities, the CEE values of Beijing, Tianjin, Baoding

⁴ State Council. 2014 government work report. http://www.gov.cn/guowuyuan/2014-03/14/content_2638989.htm.

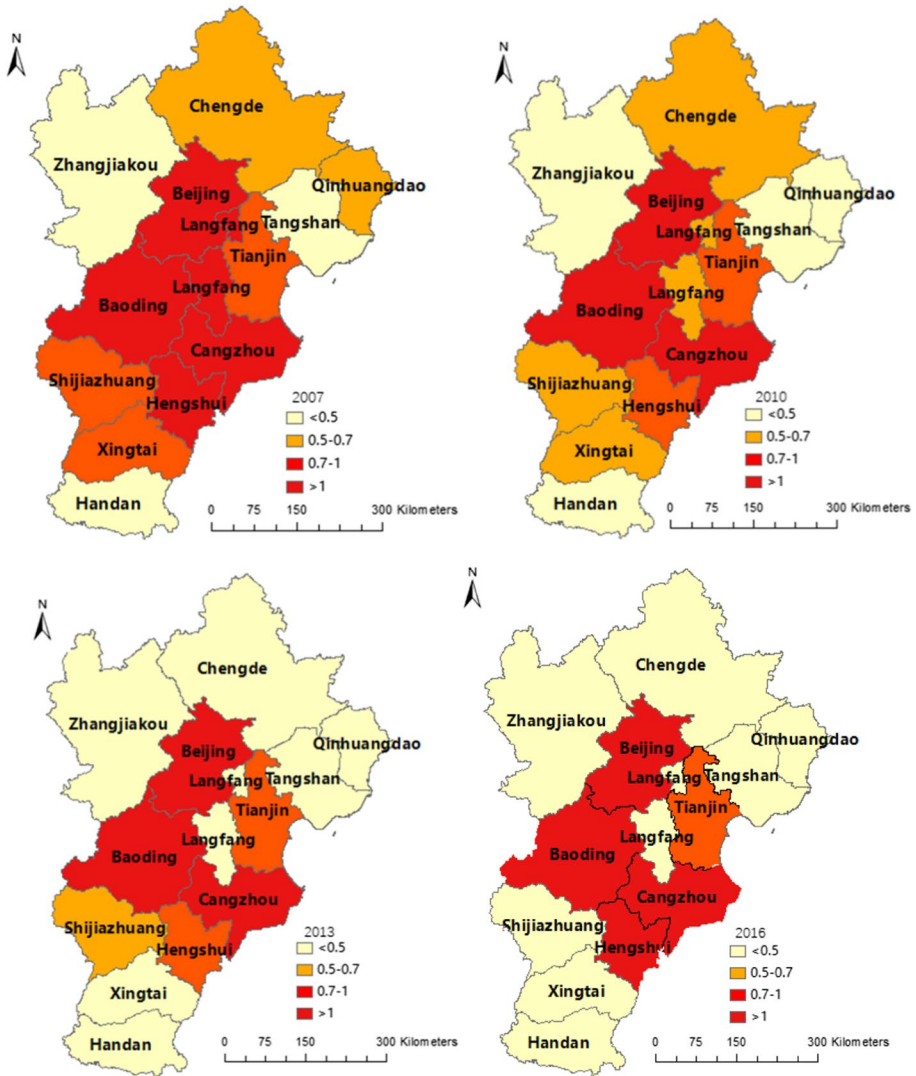


Fig. 4 CEE distribution map in BTH region

have steadily maintained high levels. However, the CEE values for Langfang have gradually weakened, moving from high efficiency in 2007 to low efficiency in 2016. As such, particular attention needs to be paid to this area (Fig. 3).

3.1.2 The spatial effect relationship of CEE

The global Moran's I values of CEE in the BTH region from 2007 to 2016 are calculated according to Eqs. (3)–(5) (Table 3). It can be seen that the overall CEE of the BTH region has a positive spatial correlation, and that it passed the test at the 5% significance level for

Table 3 Global Moran's I of CEE in BTH

	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
<i>I</i>	0.3008	0.3454	0.4189	0.2584	0.2153	0.2640	0.1582	0.1483	0.1447	0.1590
<i>P</i>	0.0052	0.0036	0.0068	0.0013	0.0019	0.0011	0.0024	0.0038	0.0037	0.0023

2007–2016. Furthermore, the BTH's region's CEE has a significant overall agglomeration characteristic. The distribution of high-value areas and low-value areas is relatively clear. The central region represented by Beijing has been at the high level of CEE, while the regional efficiency values at the northern and southern regions are lower, and the degree of agglomeration in these regions shows fluctuates. Between 2010–2011 and 2013–2015, the global Moran's I in the BTH region showed a downward trend, while between 2007–2009, 2011–2012, and 2015–2016, the global Moran's I in the BTH region showed an upward trend. The peak of agglomeration appeared in 2009, and it was the end of the upward trend of agglomeration in 2007–2009. The reason is that the 2008 Beijing Olympics accelerated the integration of BTH, and the docking and complementarity of industrial structures were realized in Beijing, which promoted the spatial agglomeration of CEE. This high degree of regional cooperation only lasted until 2009. Since 2010, the overall concentration of CEE has been on a downward trend. In response to this trend, the Chinese government proposed a national strategy for the coordinated development of BTH in 2014. By 2016, the concentration of CEE began to slowly increase. Due to many factors such as the adjustment of industrial structure, ecological governance, and market demand, in 2015, CEE showed a trend of "stagnation before starting."

The global Moran's I does not specifically indicate the spatial agglomeration characteristics of the region, so the local agglomeration characteristics should be further analyzed and studied. Geoda software was used to calculate the local Moran's I from 2007 to 2016, and a local Moran scatter plot for four years was generated, as shown in Fig. 5.

From the analysis of Fig. 5, it can be seen that the local spatial agglomeration status of CEE in the BTH region has changed significantly in the four years studied. Among the four years selected, the cities in BTH are distributed in the first and third quadrants, indicating that the H–H and L–L regions account for a large proportion of the cities, reaching more than 3/4 of the total number tested, indicating that the cities have a significant driving or inhibiting effect. In the selected years, there were fewer L–H cities in the BTH region and no H–L cities existed. From 2007 to 2010, the number of cities with H–H CEE concentration in the BTH region decreased by one, and the number of cities with L–H concentration increased by one. After that, from 2010 to 2016, the number of CEEs in cities in the BTH region remained unchanged in cities of different agglomeration types. After further analysis, in 2007–2010, Langfang's CEE changed from H–H agglomeration to L–H agglomeration; although the number of cities with different types of agglomeration remained unchanged from 2010 to 2016, the types of CEE agglomeration in some cities changed. In 2013–2016, Shijiazhuang's CEE changed from H–H agglomeration to L–H agglomeration, and Tianjin's CEE changed from L–H agglomeration to H–H agglomeration. CEE agglomeration types in cities such as Beijing, Baoding, and Cangzhou have been relatively stable for four years.

In 2016, the spatial distribution characteristics of CEE in the BTH region are reflected in the following four aspects: (a) High-efficiency cities such as Beijing, Baoding, Cangzhou, Hengshui, and Tianjin are surrounded by other high-efficiency cities.

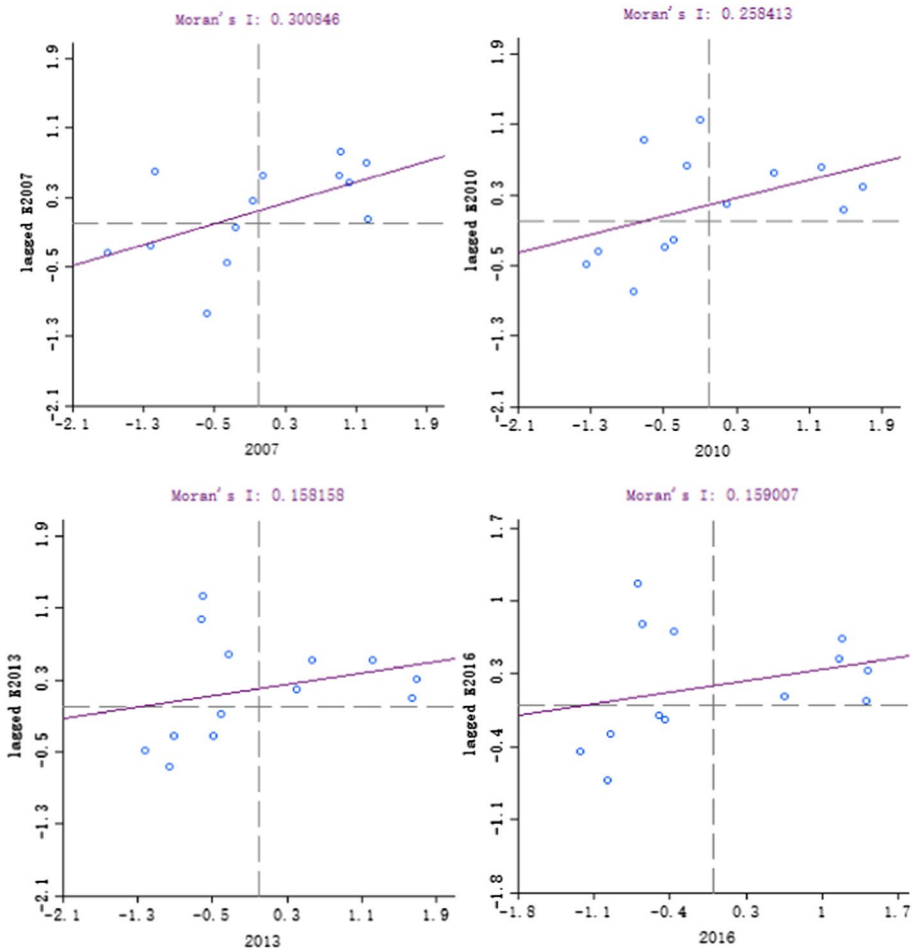


Fig. 5 Local Moran scatter plot in 2007, 2010, 2013, and 2016 of BTH region

These cities are located in the central region of BTH, and the CEE of this region is in the leading position in the BTH region; (b) low-CEE cities such as Langfang, Shijiazhuang, and Zhangjiakou are surrounded by high-CEE cities, and almost all of these cities' CEE are lower than that of neighboring cities. The surrounding high-efficiency cities could support them in various ways to improve their CEE. Among them, Shijiazhuang, as the capital city of Hebei Province, has better policy guidance and financial support but has not paid attention to the concept of green collaboration while developing, so it was reduced from a H–H city to a L–L city, something that should attract attention; (c) there were no H–L cities in the four years observed; (d) as low-efficiency cities, Xingtai, Tangshan, Qinhuangdao, and other cities are surrounded by other low-efficiency cities.

Table 4 Descriptions of influencing factors

Indicator	Ave	Min	Max	Std	Description
URB	27.86	16.53	44.59	6.92	Comprehensive urbanization rate (%)
RGDP	11.10	-1.96	29.16	6.73	GDP growth rate (%)
PGDP	9.36	1.27	684.06	59.69	Population demand of GDP (10 ⁴ yuan)
DS	40.57	5.67	65.37	7.87	Final consumption expenditure/GDP (%)
ISG	42.41	16.12	56.19	8.98	Industrial value added/GDP (%)
FDI	2.00	0.15	8.08	1.79	Foreign direct investment/GDP (%)
TEL	23.00	0.40	287.80	58.34	Science and technology expenditure (10 ⁸ yuan)

3.2 Influencing factors of CEE

3.2.1 Selection and examination of factors affecting CEE

This paper has used the super-efficiency EBM model to measure the CEE of the BTH region from 2007 to 2016 and has analyzed the characteristics of the region in terms of their spatio-temporal effects. In order to further explore the influencing factors of CEE in the BTH region, according to the three aspects of scale effect, structural effect, and technical effect of environmental quality influencing factors proposed by Grossman and Krueger (Grossman & Krueger, 1991), the level of urbanization (URB), the rate of economic growth (RGDP), GDP per capita (PGDP), final consumption rate (DS), industrial growth share (ISG), foreign direct investment (FDI), and technology investment (TEL) were selected as the influencing factors of CEE in the region. Table 4 shows the specific descriptions and the descriptive statistics for each influencing factor.

It can be seen that the standard deviations of most indicators are relatively low, indicating that there are relatively small differences in urbanization, consumption level, industrialization, and some other aspects among cities in BTH region, which proves that the development is relatively balanced, while the standard deviations of PGDP and TEL are relatively high, which are 56.69 and 58.34, respectively. It indicates that the economic development and technological level are quite different in BTH region. Therefore, in further analysis, we should focus on economic and technical indicators, and for other indicators, we should be able to better identify the impact of differences in details on CEE.

In order to avoid the problem of multicollinearity among influencing factors to improve the reliability of regression results, it is necessary to conduct a correlation test. The Pearson correlation coefficient reflects the degree of linear correlation between indicators. The coefficient value is from -1 to 1, and when the absolute value of the coefficient is closer to 1, the correlation between indicators is greater. Figure 6 shows the Pearson correlation heat map of influencing factors.

According to Fig. 6, the correlation between TEL and ISG is relatively high and shows a negative correlation, with a correlation coefficient of -0.66. This is because the development of industry and technology is often complementary to each other. However, considering that these two indicators reflecting the structural effect and the technological effect, respectively, both of them should be retained in the study. In addition, the correlations between other influencing factors are relatively small. Therefore, all indicators in the correlation test pass the test. In general, it suggests that there is no

Fig. 6 Correlation heat map of influencing factors

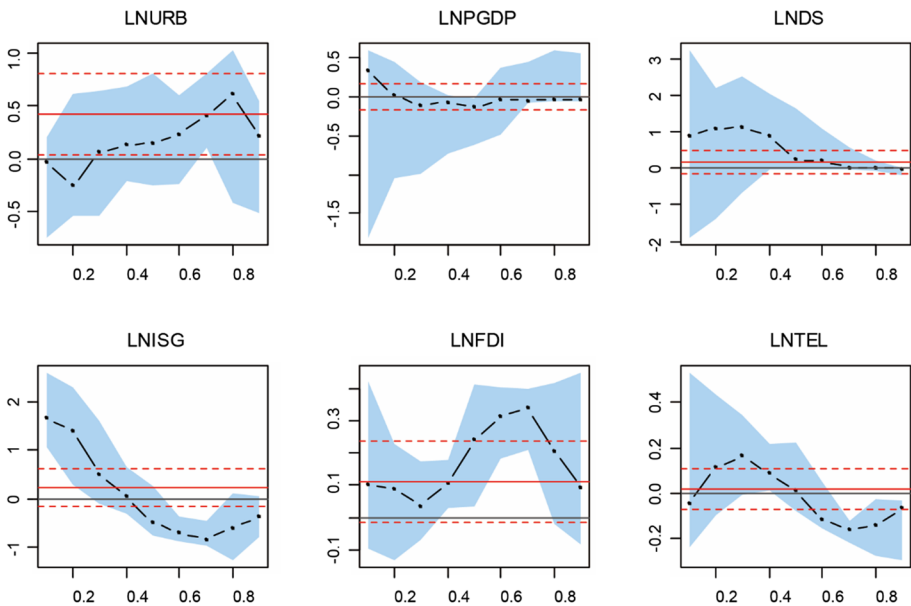
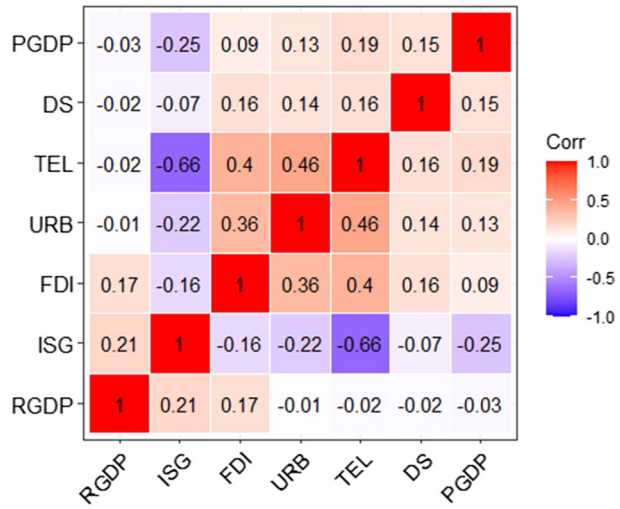


Fig. 7 Quantile regression estimation of influential factors of city-level CEE in BTH region

serious multicollinearity problem between the indicators. Next, the Jarque–Bera test is performed on the influencing factor indicators to determine that the indicator data have a sharp peak and thick tail distribution, to be suitable for quantile regression analysis. The results show that all indicators except RGDP have passed the Jarque–Bera test at a 5% significant level. As such, the quantile regression coefficient graphs of the 6 influencing factors are drawn using R language software, as shown in Fig. 7.

Table 5 Regression results of spatial quantile regression model

Variables	Penal OLS	Spatial quantile regression				
		0.1	0.25	0.5	0.75	0.9
LNURB	0.4217	- 0.1818	- 0.0660	0.1552	0.4134*	0.5256*
LNP GDP	0.0034	0.4164**	0.0668*	- 0.0624	0.0546	- 0.0150
LNDS	0.1822	1.0820**	1.5680***	0.6721	0.0432	- 0.0035
LNISG	0.2320	1.8776***	0.8282**	- 0.2306	- 0.7724***	- 0.5324**
LNFDI	0.1107	0.1416*	- 0.0431	0.1333*	0.3584***	0.1821**
LNTEL	0.0198	- 0.0507	0.1497***	0.0324	- 0.1918***	- 0.1236*

It can be seen that the conditional distribution of CEE in the six graphs has obvious differences between different quantiles, that is, the regression estimation coefficient of each influencing factor on CEE varies with the change of quantile, indicating that quantile regression can provide more abundant information. Specifically, the impact coefficient of URB fluctuates with the quantile, and changes from negative to positive, indicating that the level of urbanization has an inhibitory effect on CEE in the low-quantile area and promotes CEE in the high-quantile area. The coefficient of PGDP is relatively stable, and changes from positive to negative, indicating that CEE increases with the economic level only in a few low-quantile areas, while it has the opposite effect in most high-quantile cities. The evolution trends of coefficients of DS and ISG with quantile are similar as that of PGDP, so the influence effects are similar of the three. The coefficient of FDI fluctuates strongly with the quantile, and all values are positive, reaching the maximum at the 0.7 quantile. It indicates that the impact of FDI on CEE varies greatly at different quantiles, and the impact is greatest around 0.7 quantile. The coefficient of TEL fluctuates around 0 with the quantile. Overall, TEL has a positive promotion effect on the low-quantile area of CEE and a negative inhibitory effect on the high-quantile area.

3.2.2 Analysis of influencing factors on the spatial effects of CEE

Figure 7 shows the overall trend of the changes in the CEE coefficients of the six influencing factors at different points. In order to conduct a more specific and in-depth analysis, a spatial quantile regression model on CEE, URB, PGDP, DS, ISG, FDI, and TEL is established, as shown in Eq. (9).

$$\begin{aligned}
\ln CEE_{i,t} = & \rho(\tau) \sum_{j=1}^n w_{i,j} \ln CEE_{i,t} + \alpha + \beta_1(\tau)(\ln URB_{i,t}) + \beta_2(\tau)(\ln PGDP_{i,t}) + \beta_3(\tau)(\ln DS_{i,t}) + \beta_4(\tau)(\ln ISG_{i,t}) \\
& + \beta_5(\tau)(\ln FDI_{i,t}) + \beta_6(\tau)(\ln TEL_{i,t}) + \varphi_1(\tau) \sum_{j=1}^n w_{i,j} \ln URB_{i,j,t} \\
& + \varphi_2(\tau) \sum_{j=1}^n w_{i,j} \ln PGDP_{i,j,t} + \varphi_3(\tau) \sum_{j=1}^n w_{i,j} \ln DS_{i,j,t} \\
& + \varphi_4(\tau) \sum_{j=1}^n w_{i,j} \ln ISG_{i,j,t} + \varphi_5(\tau) \sum_{j=1}^n w_{i,j} \ln FDI_{i,j,t} \\
& + \varphi_6(\tau) \sum_{j=1}^n w_{i,j} \ln TEL_{i,j,t} + \mu_i + \lambda_t + \varepsilon_{i,t}
\end{aligned} \tag{9}$$

where the meanings of the relevant parameters are the same as formula (8). Since the research object of this study contains 13 research units, five quantile points are selected, which are 0.1, 0.25, 0.5, 0.75, and 0.9, respectively.

The spatial quantile regression results are shown in Table 5, and the general panel OLS regression results are listed for comparison. *, **, and ***, respectively, denote significance at different levels (10%, 5%, and 1%).

According to Table 5, all of the regression coefficients obtained by panel OLS regression are not significant, while they are significant in at least two quantiles by spatial quantile regression. This proves that the general mean regression is difficult to accurately reflect the actual situation, and the quantile regression can make up for this defect. Then, the analysis and discussion of the influencing factors are carried out in detail.

- (1) *Urbanization* The indicator URB in this study reflects the comprehensive urbanization degree of population, roads, and urban built-up area. It can be seen that the estimated coefficient of URB is significant and positive in the high-quantile area, indicating that the promotion of urbanization in high-CEE areas is conducive to improving CEE in BTH region. This is because in areas with relatively high CEE, such as Beijing, where urban development is relatively complete, intensive energy use is the main form of energy consumption. This can not only effectively reduce energy waste, but also improve the degree of control over energy use. Therefore, the urbanization of these areas has a positive effect on CEE.
- (2) *Economic development* PGDP and DS are indicator reflecting economic development. According to Table 5, the estimated coefficients of PGDP and DS are significant and positive in the low-quantile area, indicating that economic development in low-CEE areas is conducive to increasing CEE in BTH region. This is because low-CEE cities such as Tangshan and Handan mainly rely on high-energy-consuming and high-emission industries such as steel for their economic development. Under the Beijing-Tianjin-Hebei integration strategy, with the capital Beijing's environmental governance in surrounding areas, economic development such as Tangshan pays more attention to cleanliness and efficiency. Therefore, economic development in low-CEE regions has a positive effect on the improvement of CEE.
- (3) *Industrialization* ISG is the contribution degree of industrial added value to the regional GDP, which reflects the industrialization level of a region. The coefficient of ISG is significant in most quantiles except for the 0.5 quantile and is positive in low-CEE areas and negative in high-CEE areas, according to Table 5. It indicates that the degree of industrialization has a significant impact both in high-CEE and low-CEE areas in

BTH region, and when the level of industrialization becomes higher, the CEE of the low-CEE regions will increase; on the contrary, the CEE of the high-CEE regions will decrease. Generally speaking, the industrial industry belongs to the secondary industry, and the increase in its proportion should have a negative inhibitory effect on CEE. The opposite is true in low-CEE regions. This is because in low-CEE cities such as Tangshan, the proportion of industrial output value is already quite large, reaching about half of the total regional output value. In this case, fierce competition among industrial enterprises will stimulate production efficiency. Therefore, when the industrial output value continues to increase, it is actually the improvement of production technology and production efficiency, which will increase CEE instead.

- (4) Foreign direct investment. FDI reflects the introduction and utilization of foreign capital by cities. The coefficient of FDI is significant and positive in most quantiles except for the 0.25 quantile, indicating that utilizing foreign capital is conducive to increasing CEE. This is because the foreign capital introduced in BTH region often possesses some new technologies and advanced management concepts, which can promote the technological upgrading and management upgrading of relevant local industries. Therefore, the BTH region should continue to maintain introducing foreign investment with high standards and high quality in order to promote the improvement of CEE.
- (5) *Technological investment* Technological investment drives technological progress, although we would expect it to have a positive effect on CEE. According to Table 5, the coefficient of TEL is significant and positive in 0.25 quantile and negative in high quantiles, indicating that technology investment has different impact mechanisms on CEE at different quantiles. This is because the technological investment into this area has not met the level of scientific and technological support required for productivity enhancement. This therefore still inevitably results in industrial production being accompanied by higher levels of energy consumption and greenhouse gas emissions. Investment in science and technology should focus on energy-intensive industries by helping high-emission industries establish scientifically based and environmentally friendly energy-saving management measures.

4 Conclusions and policy implications

This paper uses qualitative and quantitative analysis methods to measure and analyze the carbon emissions efficiency (CEE), spatio-temporal effects, and influencing factors for 13 cities in the BTH region of China. The main conclusions are as follows: (a) The CEE of the BTH region has shown a generally downward trend from 2007 to 2016, and three types of evolution trajectories have been identified: stationary, fluctuating, and declining. (b) The overall spatial distribution pattern of CEE was not significantly different for the different periods, and the development of CEE in the same region in different periods was more significant. Beijing, Tianjin, Cangzhou, Baoding, and Hengshui were at the forefront of CEE values. Zhangjiakou, Tangshan, and Handan were shown to be carbon inefficient regions. (c) The CEE of BTH has significant spatial effects, manifested in spatial interaction and dependence of CEE between cities. The global spatial agglomeration characteristics are significant, and the degree of agglomeration shows a fluctuation trend. The local spatial agglomeration of CEE in the BTH region is mainly dominated by H-H and L-L cities, and

the local spatial agglomeration status has not changed significantly. Except for Langfang, Shijiazhuang, and Zhangjiakou, the local Moran' I patterns are relatively stable. (d) With respect to the various influencing factors, URB and FDI are significantly positive in high-CEE cities, PGDP and DS significantly positive in low-CEE cities, while ISG and TEL are significantly positive in low-CEE cities and negative in high-CEE cities.

The coordinated development of Beijing-Tianjin-Hebei has broken regional restrictions of CO₂ reduction. As such, the characteristics of the spatio-temporal effects of CEE in the BTH region were analyzed. It is of great significance for carrying out macro-control and taking precise measures of the carbon emission levels of cities, thereby improving the overall CEE level in the BTH region. Based on the analysis above, the following policy recommendations are proposed.

From a macroperspective, since China is still a developing country, some crucial factors such as its industrial structure, the educational level of its population, and the country's scientific and technological level, etc., cannot be rapidly improved over the short term in the BTH region. However, China's coal-based energy structure and its industrial structure, which is centered primarily on secondary industry, result in the BTH region having high levels of greenhouse gas emissions. As such, it is important that the BTH region actively explores ways to balance economic growth and low-carbon development and promotes a green and healthy development between regions. It is particularly crucial to coordinate the ways in which society, the economy, and the environment develop as a whole, and to direct green and low-carbon development from the legal, technical, and conceptual levels.

In terms of local control, considering the significant differences in CEE between the cities in BTH region, it is necessary to promote the complementary advantages across cities. Differentiate management and control, and the implementation of policies in accordance with local conditions will be more effective in terms of reducing emissions. For cities with lower CEE, such as Tangshan and Handan, the focus should be on accelerating economic development, raising consumption levels, improving industrial structure, and upgrading technology. For cities with higher CEE, such as Beijing and Baoding, the focus should be on accelerating the process of urbanization, optimizing the industrial structure, introducing high-quality foreign investment, and increasing investment in high-tech R&D. In addition, because low-efficiency cities have high-emission reduction potential, it will be easier to achieve related results to improve the CEE levels of low-efficiency cities, thereby improving the overall CEE of the BTH region. For example, through high-efficiency cities such as Beijing and Tianjin, the neighboring low-efficiency cities such as Zhangjiakou and Langfang will gradually develop into highly efficient cities. And furthermore, the development model of the central high-efficiency cities will also spread to surrounding cities, benefiting Langfang and other places. At the same time, low-efficiency cities should take the initiative and study the development experiences of cities such as Tianjin that have made successful transitions from low-efficiency to high-efficiency cities.

Appendix 1

See Table 6

Table 6 Results of CEE of 13 cities in BTH region

Cities	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	Average
Beijing	1.13	1.185	1.07	1.153	1.118	1.123	1.259	1.24	1.107	1.122	1.151
Tianjin	0.763	0.784	0.849	0.731	0.796	0.831	0.791	1.002	0.855	0.842	0.824
Shijiazhuang	0.792	0.671	0.841	0.588	0.601	0.587	0.507	0.503	0.505	0.46	0.606
Tangshan	0.298	0.339	0.417	0.265	0.282	0.311	0.282	0.283	0.253	0.242	0.297
Qinhuangdao	0.614	0.609	0.536	0.394	0.372	0.396	0.263	0.246	0.218	0.231	0.388
Handan	0.438	0.395	0.442	0.222	0.216	0.244	0.163	0.156	0.134	0.138	0.255
Xingtai	0.709	0.571	0.61	0.505	0.566	0.496	0.446	0.466	0.466	0.431	0.527
Baoding	1.036	1.209	1.099	1.223	1.135	1.14	1.283	1.275	1.123	1.126	1.165
Zhangjiakou	0.453	0.471	0.508	0.431	0.425	0.438	0.399	0.394	0.376	0.35	0.425
Chengde	0.682	0.608	0.618	0.538	0.588	0.575	0.475	0.493	0.463	0.408	0.545
Cangzhou	1.121	1.196	1.042	1.074	1.069	1.069	1.101	1.081	1.047	1.037	1.084
Langfang	1.039	1.012	1.019	0.634	0.587	0.638	0.404	0.402	0.306	0.336	0.638
Hengshui	1.069	1.104	0.834	0.901	0.95	1.014	0.85	0.933	1.009	1.029	0.969
Average	0.780	0.781	0.760	0.666	0.670	0.682	0.633	0.652	0.605	0.596	0.683

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