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Analysis of CO_2 Emission Performance and Abatement Potential for Municipal Industrial Sectors in Jiangsu, China

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Abstract: As the main source of CO_2 emissions in China, the industrial sector has faced pressure for reducing emissions. To achieve the target of 50% reduction of industrial carbon intensity by 2020 based on the 2005 level, it is urgent to formulate specific CO_2 emission mitigation strategies in the provincial industrial sector. In order to provide decision-making support for the development and implementation of mitigation policy, our undesirable slack based measure (SBM) model is firstly applied to evaluate the industrial CO_2 emission efficiency under total-factor frame (TFICEE) in 13 prefecture-level cities of Jiangsu Province, the largest CO_2 emitter in China. Then, we analyze space-time distribution and distributional evolution tendency of TFICEE by using the GIS visualization method and kernel density estimation, respectively. Finally, we utilize the industrial abatement model to estimate the CO_2 abatement potential of Jiangsu's industrial sector. The empirical results show that there exists a significant spatial inequality of TFICEE across various regions in Jiangsu, but the regional disparity has been narrowing during our study period. Additionally, average annual industrial CO_2 emission reductions in Jiangsu Province can attain 15,654.00 (ten thousand tons), accounting for 28.2% of its average annual actual emissions, which can be achieved by improving production technology, adjusting industrial structure and raising the level of industry concentration.

Keywords: industrial CO_2 emission performance; industrial abatement potential; regional disparity; SBM-Undesirable model; GIS

1. Introduction

With increasingly serious global climate anomalies, climate change has become one of the most severe challenges faced by humankind in the 21st century. An increasing number of countries are concerned with mitigating energy consumption and CO_2 emissions. In particular, China, the world's largest CO_2 emitter since 2007, accounted for 28% of global total CO_2 emissions in 2013 [1], as a result of its rapid urbanization and industrialization. Since entering the middle stage of industrialization, the industrial sector has become the pillar of China's economy, and meanwhile, industrial CO_2 emission (ICE) has been the main source of national CO_2 emissions [2,3]. Thus, how to effectively reduce ICE is a key to achieving the national CO_2 emission reduction targets. In order to tackle climate change and extenuate the rapid growth of ICE, China promised to abate its industrial carbon intensity (defined as CO_2 emissions per unit of industrial added value) by 50% of 2005 levels by 2020 in 2014 [4].

Policy makers have realized that regional disparity, which is caused by imbalanced socioeconomic conditions as well as physical geography, brings difficulties and uncertainties to the development and implementation of mitigation policies [5–7], and becomes an obstacle to the realization of national emission reduction. Therefore, it is worth investigating distributional characteristics and regional inequality of ICE. Considering that CO_2 emission efficiency can reflect the level of economic returns motivated by per unit CO_2 emission, evaluating and improving CO_2 emission efficiency has recently drawn increasing attention from the related scholars. The most commonly used measurement for macro-economy CO_2 emission efficiency is partial-factor emission efficiency analysis, which mainly refers to carbon intensity [8–10]. Recently, a growing number of studies have concentrated on the evaluation of total-factor CO_2 emission efficiency [11–15], since any economic production process can be considered as a joint production process in which diverse inputs of energy and resources are employed to generate diverse desirable outputs (e.g., gross industrial output) and undesirable outputs (e.g., CO_2 emissions). For instance, Wang et al. [15] applied directional distance function as well as Luenberger productivity index to analyze the total-factor carbon emission performance of industrial land use in China.

Data envelopment analysis (DEA) has been accepted as a popular tool for evaluating total-factor CO_2 emission efficiency because it evaluates emission efficiency within a total-factor productivity framework, which is more appropriate than the partial-factor indicator method. Numerous DEA models have been developed and applied to evaluate CO_2 emission efficiency by more and more academic researchers. Among these DEA models, the undesirable slack based measure (SBM) model [16] proposed by Tone has received increasing attention for its superiority in evaluating efficiency [17–20]. The SBM-Undesirable model can not only eradicate the radial and oriented deviation of traditional DEA models, but also be applicable for evaluating efficiency in the presence of undesirable outputs that are unavoidable in modern production. For instance, Choi et al. [18] estimated CO_2 emission efficiency and potential reductions for China during 2001–2010 by using a non-radial SBM model.

On the other hand, the estimation of CO_2 abatement potential is also critical for formulating appropriate mitigation policies, and provides policy makers with decision-making support for setting its reduction targets for 2020. Generally, CO_2 abatement potential can be seen as an undeveloped emission reduction capacity of the emitter, which refers to the volume of CO_2 emissions that can be avoided through implementation of abatement technologies [21]. The studies on CO_2 emission abatement potential estimation have employed several methodologies [22–24]. Among the various methods, the DEA efficiency variance estimating method has attracted the most attention. According to the DEA theory, efficiency frontier is constituted by efficient decision making units (DMU), while inefficient DMUs can reach the frontier and become efficient by reducing excessive input which is generally viewed as potential emission reductions. So far, DEA has been frequently used to estimate the CO_2 abatement potential of different regions and various sectors [25–29]. For instance, Yu and Zhang [26] worked out energy efficiency and CO_2 abatement potential of China's industrial sector by using the directional distance function and DEA method. Bi et al. [28] utilized a non-radial DEA model characterized with multidirectional efficiency analysis to investigate provincial energy and environmental efficiency, energy saving and CO_2 abatement potential of China's transportation sector. Du [29] analyzed energy efficiency, energy saving and CO_2 abatement potential for China's 29 regions and three areas within ecological total-factor framework by using the super-efficiency SBM model.

As the industrial sector contributes the most CO_2 emissions, several studies have focused on the analysis of CO_2 emission efficiency and abatement potential for China's industrial sector [30–36]. For instance, Wang and Wei [33] analyzed the regional energy and emission efficiency, the energy saving and CO_2 abatement potential, and the marginal abatement costs of industrial CO_2 emissions of 30 Chinese major cities. Likewise, as the largest emitter in China [37], Jiangsu Province has attracted the attention of many scholars on CO_2 emission issues [37–39]. For instance, Wang et al. [39] analyzed the influencing factors of energy-related CO_2 emissions in Jiangsu Province during 1995–2009 by using the Log Mean Divisia Index (LMDI) method. However, these studies have mainly focused on exploring the influencing factors of CO_2 emissions in Jiangsu, but paid little attention to the analysis of

CO_2 emission performance and abatement potential. Worse, as far as we know, the relevant studies of Jiangsu's municipal industrial sectors are blank. Therefore, it is necessary and urgent to fill the gap for the decarbonization transition of Jiangsu's industrial sector and effective implementation of mitigation policies.

Under such circumstances, in this paper, we aim to study Jiangsu's industrial CO_2 emission performance in greater depth by analyzing the levels, space-time distribution and distributional evolution tendency of the industrial CO_2 emission efficiency under total-factor frame (TFICEE) in 13 prefecture-level cities of Jiangsu, and estimate abatement potential of industrial CO_2 emission (APICE) and potential emission reductions for various regions in Jiangsu Province.

The paper is organized as follows. Section 2 introduces models including the SBM-Undesirable model, kernel density estimation and the industrial abatement model. Section 3 presents the empirical study including variable selection, data collection and treatment, analysis of CO_2 emission performance and measurement of industrial abatement potential. Section 4 draws the conclusions.

2. Methodology

2.1. Environmental Production Technology

Environmental production technology can be considered as a possible production set containing both desirable and undesirable outputs, which denotes the technical relationship between desirable outputs, undesirable outputs and inputs. Supposing a production process that uses capital (K), energy (E) and labor (L) as inputs to produce desirable output (G) and undesirable output (C), environmental production technology can be described as follows:

$$T = \{(K, E, L, G, C)\ : (K, E, L)\ \text{can produce}\ (G, C)\}. \tag{1}$$

According to Zhou et al. [40], we further specify the environmental production technology for J DMUs in Equation (2), by assuming that the production technology exhibits constant returns to scale [25,41].

$$T = \left\{ \begin{array}{c} (K, E, L, G, C) : \sum_{j=1}^{J} \lambda_j K_j \leqslant K, \quad \sum_{j=1}^{J} \lambda_j E_j \leqslant E, \quad \sum_{j=1}^{J} \lambda_j L_j \leqslant L, \\ \sum_{j=1}^{J} \lambda_j G_j \geqslant G, \quad \sum_{j=1}^{J} \lambda_j C_j \leqslant C, \quad \lambda_j \geqslant 0,\ j = 1, 2, \ldots, J \end{array} \right\}, \tag{2}$$

where λ_j is the weight variable that is utilized to construct a convex combination enveloping all DMUs. J denotes the total number of DMU.

2.2. SBM-Undesirable Model

DEA has been widely applied in various fields for solving the problem of efficiency evaluation, since the traditional CCR (Charnes, Cooper and Rhodes) [42] and BCC (Banker, Charnes and Cooper) [43] models were proposed. Traditional DEA models are essentially the radial and oriented measurement methods, which generally result in overestimation of efficiency. In order to address the problem, Tone proposed that the SBM [44] model, a non-radial and non-oriented DEA model, which can solve the defects of the traditional DEA model so as to reflect the nature of the efficiency evaluation. Actually, the modern production process is often accompanied by undesirable outputs such as waste water, exhausted gas and so on, so Tone proposed a modified DEA scheme [16] for evaluating efficiency in the presence of undesirable outputs based on the SBM model, i.e., the so-called SBM-Undesirable, which is presented in Equation (3):

$$
\begin{aligned}
&\min\rho_0 = \frac{1-\frac{1}{M}\sum_{m=1}^{M} S_m^-/x_{m0}}{1+\frac{1}{N+T}\left(\sum_{n=1}^{N} S_n^+/y_{n0}+\sum_{t=1}^{T} S_t^-/b_{t0}\right)},\\
&\text{s.t.}\quad \sum_{j=1}^{J}\lambda_j x_{mj}+S_m^- = x_{m0},\quad m=1,\,2,\,\ldots,\,M,\\
&\sum_{j=1}^{J}\lambda_j y_{nj}-S_n^+ = y_{n0},\quad n=1,\,2,\,\ldots,\,N,\\
&\sum_{j=1}^{J}\lambda_j b_{tj}+S_t^- = b_{t0},\quad t=1,\,2,\,\ldots,\,T,\\
&\lambda_j \geqslant 0,\ S_m^- \geqslant 0,\ S_n^+ \geqslant 0,\ S_t^- \geqslant 0,\ j=1,\,2,\,\ldots,\,J,
\end{aligned}
\tag{3}
$$

where $x \in R_+^M$, $y \in R_+^N$ and $b \in R_+^T$ are vectors of inputs, desirable outputs and undesirable outputs, respectively. There are J DMUs and the observed data for DMU_j are $x_j = \left(x_{1j},\ x_{2j}, \ldots, x_{Mj}\right)$, $y_j = \left(y_{1j},\ y_{2j}, \ldots, y_{Nj}\right)$ and $b_j = \left(b_{1j},\ b_{2j}, \ldots, b_{Tj}\right)$. S_m^-, S_n^+, and S_t^- denote input excess, desirable output shortfall and undesirable output excess, respectively. λ is the weight vector and ρ_0 denotes the SBM efficiency score. Generally, producing more desirable outputs and less undesirable outputs relative to less input resources is a criterion of efficiency.

2.3. Kernel Density Estimation

As an important non-parametric method, kernel density estimation has been widely applied in studying uneven distribution [45]. Specifically, this method is mainly utilized to estimate the probability density of random variables and depict the distributional pattern of random variables with a continuous density curve. Assuming that the density function of the random variable X is $f(x)$, we can estimate it by using Equation (4).

$$f(x) = \frac{1}{Nh}\sum_{i=1}^{N} K\left(\frac{X_i - x}{h}\right), \tag{4}$$

where N is the number of observations; h denotes the bandwidth; $K(\cdot)$ presents the kernel function; X_i is observation value obeying independent and identically distributed (iid).

Generally, kernel density function is a weighting function or smoothing function. According to the different forms of expression, it can be divided into Gaussian kernel, Epanechnikov kernel, triangle kernel and so on. This article selects frequently-used Gaussian kernel function to study distributional dynamic and evolution tendency of Jiangsu's industrial CO_2 emission efficiency, and the function is expressed in Equation (5).

$$K(x) = \frac{1}{\sqrt{2\pi}}\exp\left(-\frac{x^2}{2}\right), \tag{5}$$

As a non-parametric method, kernel density estimation results are presented in the form of graphics; therefore, we study the evolution of distribution by observing distributional position, scalability and morphological changes.

2.4. Industrial Abatement Model

Based on CO_2 emission efficiency defined by Choi et al. [18] and emission reduction potential defined by Wang et al. [46] and Rao et al. [47], we propose industrial abatement model in Equation (6):

$$TFICEE_{j,t} = \frac{TICE_{j,t}}{ICE_{j,t}} = \frac{ICE_{j,t} - LICE_{j,t}}{ICE_{j,t}} = 1 - \frac{LICE_{j,t}}{ICE_{j,t}}, \tag{6}$$

where $TFICEE_{j,t}$ denotes Industrial CO_2 Emission Efficiency under Total Factor Frame of j-th city at the period of t; $TICE_{j,t}$ (Target Industrial CO_2 Emissions) represents optimal CO_2 emissions of j-th city at the period of t according to the production frontier; $ICE_{j,t}$ (Industrial CO_2 Emissions) represents actual

CO_2 emissions of j-th city at the period of t; $LICE_{j,t}$ (Loss Industrial CO_2 Emissions) denotes excessive CO_2 emissions of j-th city at the period of t compared with the frontier. Actually, it is a slack amount of CO_2 emissions and can also be considered as achievable emission reductions. $APICE_{j,t}$ denotes Abatement Potential of Industrial CO_2 Emissions of j-th city at the period of t, and can be measured by Equation (7):

$$APICE_{j,t} = \frac{LICE_{j,t}}{ICE_{j,t}}. \tag{7}$$

SBM-Undesirable model can work out $TFICEE_{j,t}$ and the values of $TICE_{j,t}$, $LICE_{j,t}$, and $APICE_{j,t}$ of 13 cities can be obtained by solving Equations (6) and (7). Obviously, the higher value of $APICE_{j,t}$ shows that the greater reduction potential and the worse environmental performance of the observed city. Clearly, $APICE_{j,t}$ and $TFICEE_{j,t}$ satisfy the relationship that $TFCEE_{j,t} + APCE_{j,t} = 1$.

3. Empirical Study

In this section, we firstly select appropriate indicators of evaluating TFICEE and collect the related data. Then, our SBM-Undesirable model is applied to work out the TFICEE of 13 cities in Jiangsu Province. In addition, we analyze space-time distribution and distributional evolution tendency of TFICEE in Jiangsu by using the GIS visualization method and kernel density estimation. Finally, we apply the industrial abatement model to estimate the regional abatement potential of Jiangsu's industrial sector.

3.1. Variable Selection

Considering that the TFICEE should reflect energy conservation, environmental protection and industrial economic growth, this paper selects five variables as the inputs and outputs. Based on the SBM-Undesirable model described in Section 2, three variables serve as inputs: labor employment (L), capital stock (K) and energy consumption (E). Gross industrial output (G) is viewed as the desirable output, while CO_2 emission (C) is taken as undesirable output. The input–output indicators are summarized in Table 1.

Table 1. Variables of inputs and outputs.

	Variable	Units
Input	Capital	100 million RMB
	Labor	10 thousand persons
	Energy	10 thousand tons of coal equivalent (10,000 tce)
Desirable output	Output	100 million RMB
Undesirable output	CO_2	10 thousand tons

3.2. Data Collection and Treatment

Jiangsu Province, consisting of 13 prefecture-level cities, can be categorized into three areas of Sunan, Suzhong and Subei, according to socioeconomic conditions and geographic distributions. Specifically, Sunan contains Nanjing (NJ), Suzhou (SZ), Wuxi (WX), Changzhou (CZ) and Zhenjiang (ZJ); Suzhong contains Yangzhou (YZ), Taizhou (TZ) and Nantong (NT); Subei contains Yancheng (YC), Huaian (HA), Suqian (SQ), Xuzhou (XZ) and Lianyungang (LYG). The data presented in this paper cover industrial input–output data of 13 prefecture-level cities in Jiangsu Province during 2004–2013, when Jiangsu experienced accelerated urbanization and industrialization. The relevant data are collected from the China Energy Statistical Yearbook [48], China City Statistical Yearbook [49], Jiangsu Economic Census Yearbook [50–52], and City Statistical Yearbooks of 13 prefecture-level cities. It should be noted that the industrial data in this paper only contain industrial enterprises above designated size, due to limitations of statistics. In order to eliminate the price effect, all nominal values are converted into 2004 constant price. A statistical description for variable data is shown in Table 2.

Table 2. Descriptive statistics of input and output variables (2004–2013).

Year		Inputs			Desirable Output	Undesirable Output
		Capital	Labor	Energy	Gross Output	CO_2
2004	Mean	1166.19	70.56	756.68	1998.87	2764.05
	Std. dev.	1286.59	68.42	568.43	2391.31	2077.53
	Max	4888.87	214.55	1715.06	8668.20	6442.85
	Min	89.03	9.47	64.50	141.26	225.17
2007	Mean	2223.64	79.08	1094.03	3744.13	3968.61
	Std. dev.	2604.51	84.80	860.35	3987.14	3082.64
	Max	9648.09	339.62	3206.62	14,868.15	11,393.35
	Min	258.43	18.93	112.79	402.23	412.91
2010	Mean	3429.63	93.54	1312.49	6102.25	4746.79
	Std. dev.	3388.69	104.40	1077.06	5417.12	3865.00
	Max	12,752.27	419.87	3827.07	21,624.27	13,506.92
	Min	691.38	24.69	119.41	997.69	436.33
2013	Mean	4397.08	88.06	1552.22	8816.90	5574.30
	Std. dev.	3852.19	75.28	1226.26	6056.60	4392.70
	Max	15,241.85	319.60	4298.04	26,327.21	15,028.32
	Min	1339.08	25.17	180.77	2598.40	653.84

Note: Due to the limited space, all annual data are not listed.

Labor employment (L) and gross industrial output (G) are directly obtained from yearbooks that are mentioned above. The estimation of capital stock (K) is generally conducted by Perpetual Inventory Method (PIM), which requires the data of industrial capital depreciation rate and initial capital stock. Due to limitations of statistics, these data need to be estimated before using the method. Therefore, in order to reduce deviation from data estimation, we choose an alternative method that selects the sum of average balance of net fixed assets and average balance of current assets as Capital stock [17]. Energy consumption (E) in this paper refers to comprehensive consumption of end-use energy, which includes raw coal, gasoline, kerosene, diesel oil, fuel oil, liquefied petroleum gas (LPG), natural gas and liquefied natural gas (LNG). All sorts of energy consumption are converted into standard coal equivalents according to conversion factors from physical units to coal equivalents that are obtained from Appendix IV of China Energy Statistical Yearbook.

Because there are no official statistics yet on CO_2 emission in China, existing literature generally uses the Reference Approach recommended by the Intergovernmental Panel on Climate Change (IPCC) to estimate the CO_2 emissions. In this paper, we also utilize the method to calculate CO_2 emissions with industrial final energy consumption, which is shown in Equation (8):

$$CO_2 \text{ emissions} = \sum\nolimits_i E_i \times NCV_i \times CEF_i \times COF_i \times (44/12), \quad (8)$$

where E_i represents the end-use of energy source, i, and NCV_i (Net Caloric Value, CEF_i (CO_2 Emission Factor), COF_i (CO_2 Oxidation Factor) stand for the heat equivalent, the carbon emission coefficient and the carbon oxidation factor, respectively. In addition, 44/12 denotes the ratio of the molecular weight of CO_2 (44) to the molecular weight of carbon (12), which is called CO_2 gasification coefficient as well.

3.3. Comprehensive Analysis of TFICEE

3.3.1. Evaluation of TFICEE

Based on the SBM-Undesirable model in Section 2, TFICEE of 13 prefecture-level cities in Jiangsu Province from 2004 to 2013 are obtained, which are listed in Table 3. At the city level, the average TFICEE scores of Changzhou and Taizhou both exceed 0.9, which are the optimal levels of efficiency in the analysis. On the contrary, Xuzhou has the lowest average TFICEE of 0.428, followed by Zhenjiang with an average TFICEE of 0.489. At the area level, Table 3 indicates that Suzhong enjoys the highest average TFICEE score of 0.858, followed by Sunan with an average score of 0.763, and the least efficient Subei with an average score of 0.645. Actually, there exist differences in economic development, industrial technology, industrial structure and local environmental policy among various cities of Jiangsu Province, and these differences may account for regional inequality of TFICEE in Jiangsu.

Table 3. TFICEE of 13 prefecture-level cities in Jiangsu Province (2004–2013).

Region	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	Mean
NJ	1.000	1.000	1.000	1.000	1.000	0.843	0.621	0.552	0.492	0.584	0.809
SZ	1.000	1.000	1.000	1.000	0.925	0.799	0.663	0.607	0.500	0.537	0.803
WX	1.000	1.000	1.000	1.000	1.000	0.791	0.667	0.608	0.484	0.526	0.808
CZ	0.656	0.828	1.000	0.926	1.000	1.000	1.000	1.000	0.767	0.894	0.907
ZJ	0.387	0.454	0.458	0.524	0.615	0.554	0.496	0.465	0.413	0.520	0.489
YZ	0.473	0.766	0.764	0.679	0.797	1.000	1.000	1.000	1.000	1.000	0.848
TZ	0.777	0.867	0.907	0.913	0.927	1.000	1.000	1.000	1.000	1.000	0.939
NT	0.401	1.000	1.000	1.000	1.000	1.000	0.669	0.620	0.547	0.647	0.788
YC	0.461	1.000	0.797	1.000	1.000	1.000	1.000	1.000	1.000	0.652	0.891
HA	0.404	0.474	0.517	0.519	0.532	0.552	0.692	0.592	1.000	0.774	0.606
SQ	0.439	0.487	0.525	0.597	0.602	0.625	1.000	1.000	1.000	1.000	0.728
XZ	0.288	0.432	0.426	0.471	0.459	0.433	0.423	0.429	0.417	0.504	0.428
LYG	0.229	0.402	0.413	0.442	0.494	0.558	0.673	0.768	0.900	0.829	0.571
Sunan	0.809	0.856	0.892	0.890	0.908	0.797	0.689	0.646	0.531	0.612	0.763
Suzhong	0.550	0.878	0.890	0.864	0.908	1.000	0.890	0.873	0.849	0.882	0.858
Subei	0.364	0.559	0.536	0.606	0.617	0.634	0.758	0.758	0.863	0.752	0.645
Jiangsu	0.574	0.764	0.773	0.787	0.811	0.810	0.779	0.759	0.748	0.749	0.755

Note that, the imbalance between the number of variables and the number of DMUs may result in a dimensionality problem. Generally, the number of DMUs should be three times greater than that of variables, which is necessary for the credibility of the DEA results. However, it should be noted that there is still a dispute about this issue and the restriction is different in some literature [53]. In addition, the DEA results are relatively reasonable as well and see no unusual phenomenon of excessive efficient DMUs resulting from the lack of DMU.

We further calculate annual average TFICEE of Jiangsu and its three areas from 2004 to 2013. The time trends for the four observations are portrayed in Figure 1. The average TFICEE of Subei almost continuously increases during 2004–2012 but has a significant decrease in 2013, the last year of our study period. The average TFICEE of Sunan slightly increases during 2004–2008, suffers a sharp decline during 2008–2012, but enjoys a significant increase in 2013. The average TFICEE of Suzhong greatly improves in 2005, and fluctuates at a high level in the rest of our study period. On the other hand, the average TFICEE of Jiangsu has a significant increase in 2005, which is caused mainly by the great efficiency improvement of Suzhong and Subei, and then slightly fluctuates around 0.750.

Combined with industrial structure, national regulation and international economic situation, a qualitative explanation for different trends of TFICEE in Subei and Sunan is given as follows: at the beginning of our study period, the carbon emission efficiency of Subei is at a low level, thereby having relatively large room for growth. Moreover, Jiangsu Province experiences a rapid economic development during our study period in which Subei absorbs advanced technology and management modes, and introduces a large number of investments and talents from Sunan and other developed regions. Therefore, Subei's carbon efficiency experiences a continuous increase from 2004 to 2012. However, in 2012, the central government proposed ecological civilization construction that largely restricts the production of high-carbon industries. Actually, the pillar of Subei's industrial structure is heavy industry, and, therefore, Subei's carbon efficiency suffers a significant decrease in 2013 due to the impact of ecological civilization construction. On the other hand, Sunan's carbon efficiency was at a high level at the beginning, thereby having limited room for growth. Nevertheless, Sunan's carbon efficiency slightly increases with the rapid economic development of Jiangsu during 2004–2008. However, the outbreak of the global financial crisis in 2008 changed the trend. Actually, Sunan's economy is export-oriented and a large number of foreign companies are greatly affected by the financial crisis. Subsequently, Sunan's carbon efficiency suffered a sharp decline during 2008–2012. With the passing of the financial crisis, the recovery of the global economy and the improvement of the international trade situation, Sunan's foreign investment and international cooperation gradually increased. As a result, the carbon efficiency of Sunan in 2013 improved significantly.

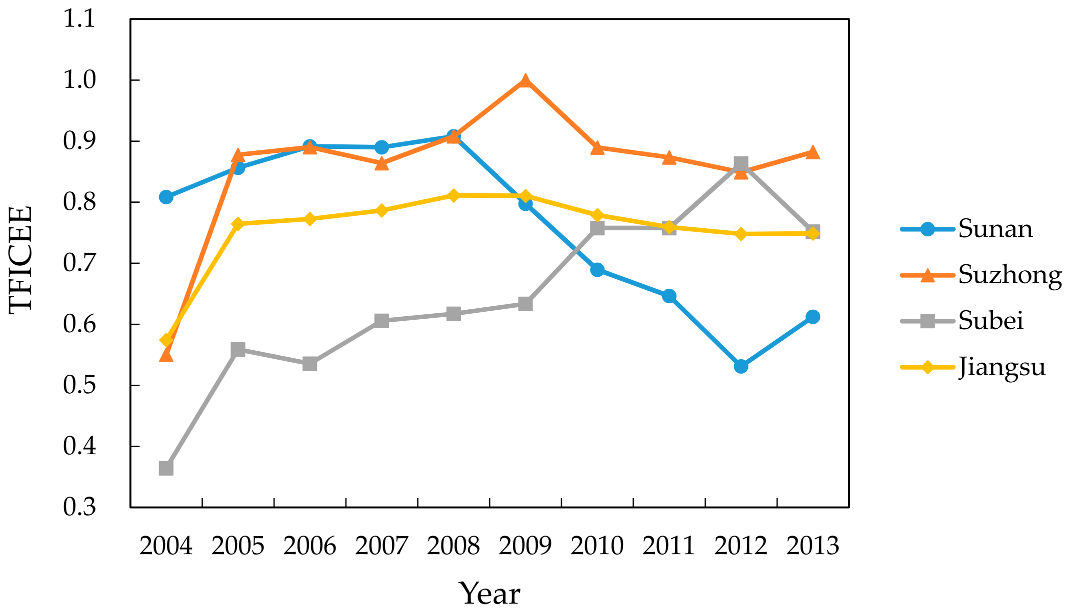

Figure 1. Time trend of TFICEE in Jiangsu Province (2004–2013).

3.3.2. Space-Time Distribution of TFICEE

In order to present an intuitive spatial distribution of TFICEE in Jiangsu and conduct dynamic analysis of performance changes during our study period, we further draw the geographic distribution graphs of TFICEE in 2004, 2007, 2010 and 2013 by using ArcGIS 10.2 (Environmental Systems Research Institute, Inc., Redlands, CA, USA), and the results are shown in Figure 2. This figure indicates that there exists a significant spatial inequality of TFICEE in Jiangsu, which first presents a decreasing trend from south to north in the distribution of 2004 and 2007, and then changes to be another decreasing trend from the middle to the north and south. In addition, in terms of performance improvement, the number of cities whose efficiencies are lower than 0.5 is eight in 2004, and then decreases to two in 2007 and 2010, while efficiencies of all cities are greater than 0.5 in 2013.

The performances of Suqian and Taizhou experience a sustained growth from 2004 to 2013 and eventually achieve efficiency. Lianyungang and Yangzhou both experience great performance improvements, which are larger than 0.5 during 2004 to 2013. In contrast, the performances of Nangjing, Suzhou and Wuxi all decrease by more than 0.5 over the period of 2004 to 2013. Additionally, there are six cities experiencing a performance fluctuating process during the study period, and the most significant fluctuation appears in Nantong and Yancheng, whose fluctuation ranges of TFICEE are both over 0.5. The remaining four cities fluctuate within a small scale over our study period. In general, Jiangsu's TFICEE levels show an upward trend during our study period.

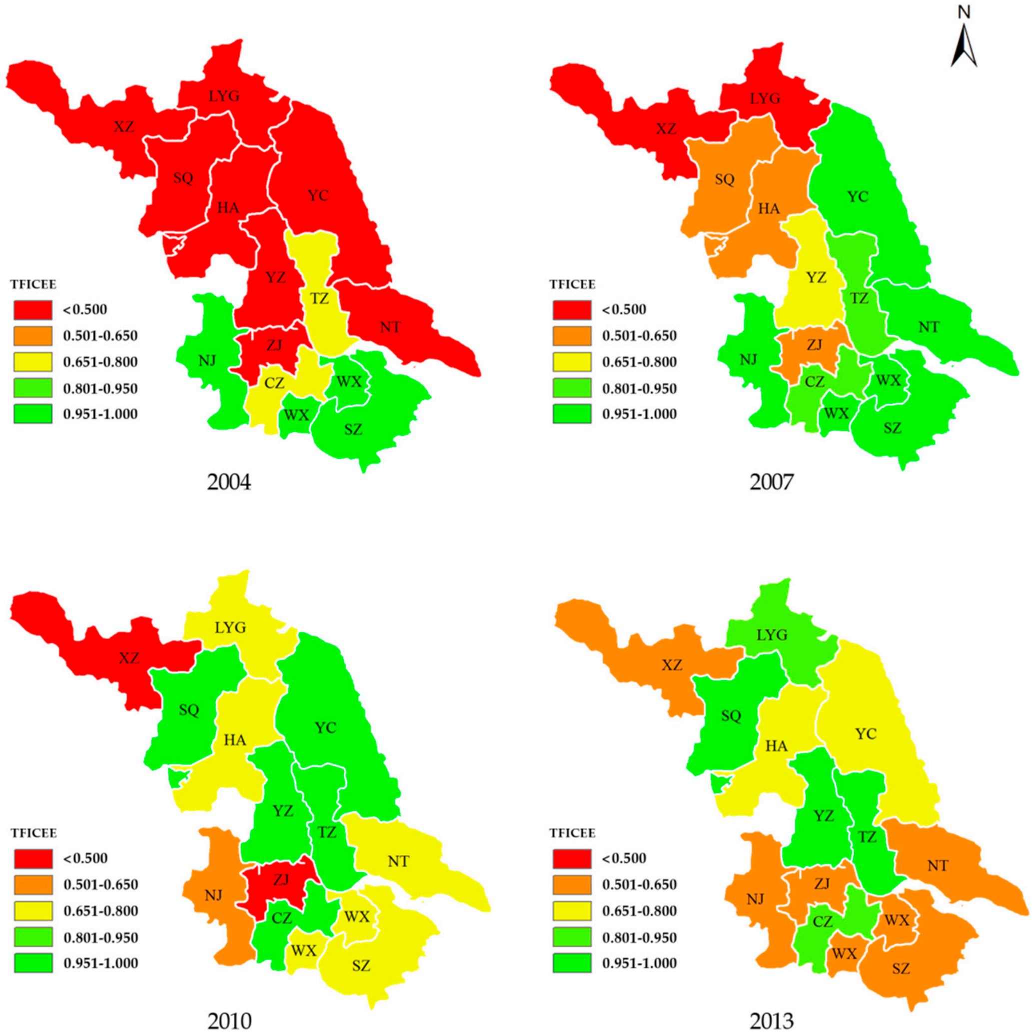

Figure 2. Spatial distribution of TFICEE in Jiangsu Province (2004–2013).

3.3.3. Distributional Evolution Tendency of TFICEE

Based on kernel density estimation in Section 2, and with the assistance of R-program (R-3.2.4, Robert Gentleman and Ross Ihaka, Auckland, New Zealand) [54,55], the kernel density estimation curves of Jiangsu's TFICEE in 2004, 2007, 2010 and 2013 are obtained, and the results are shown in Figure 3. By comparing the four curves, we can easily find that peak value and variation range have experienced a continuous increasing and shrinking, respectively, which indicate that regional disparity of TFICEE has been narrowing during our study period.

Specifically, compared with 2004, the density function of 2007 significantly moves to the right and becomes steeper; meanwhile, its variation range obviously narrows, which indicates that the overall efficiency greatly improves and regional disparity narrows during this period. However, the appearance of significant double peaks also shows that there is a serious polarization phenomenon in the distribution of TFICEE at the same time. Compared with 2007, the density function of 2010 nearly stays stationary, but its peak value and variation range change in opposite direction, indicating that there is a decline in regional disparity of TFICEE. Compared with 2010, the density function of 2013 slightly moves to the left and becomes steeper; meanwhile, the variation range shrinks and the significant double peaks disappear, indicating that regional disparity and polarization phenomenon both have been alleviated.

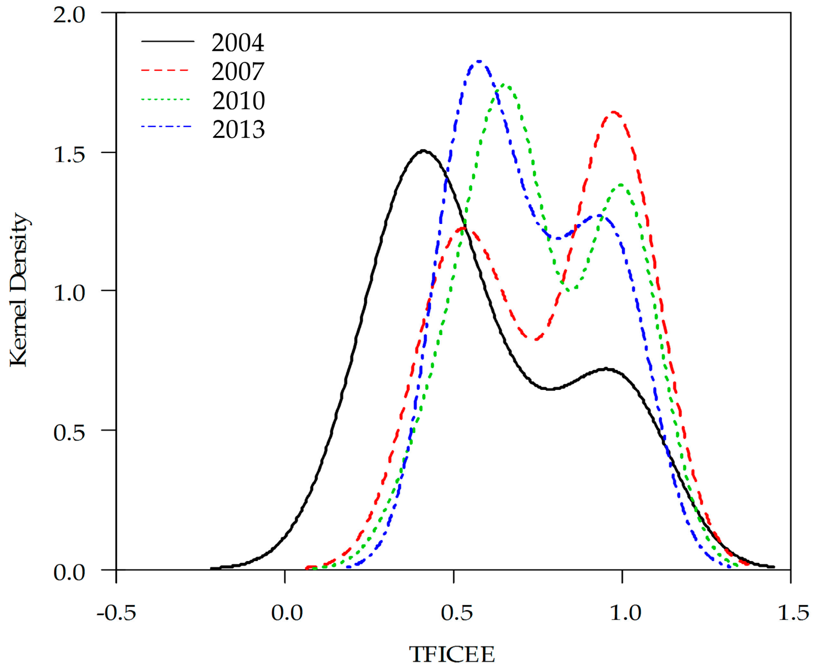

Figure 3. Distributional evolution tendency of TFICEE in Jiangsu Province (2004–2013) (Note that, the existence of density mass beyond 1 in Figure 3 is caused by the boundary effect of kernel density estimation, but we have proved that it has little effect on the results derived from this figure in this paper).

The changes of the peaks of Kernel density getting higher and ranges of TFICEE shrinking denote that regional disparity of TFICEE in Jiangsu Province has been narrowing. As mentioned above, Jiangsu has experienced a rapid economic development during 2004–2013. In addition, cooperation and exchanges among cities have been strengthened with the improvement of traffic, leading to the extension of advanced technology and efficient management modes, as well as the full flow of talents, capitals and other elements within the bounds of the entire province. As a result, the reduction in regional inequality of economic development leads to the convergence of TFICEE in Jiangsu Province, which is characterized by the increase of peak value and the shrunken ranges of TFICEE in Figure 3.

3.4. Estimation of Industrial Abatement Potential

Based on the industrial abatement model in Section 2, average annual abatement potential of industrial CO_2 emissions (APICE) and potential industrial CO_2 emission reductions of 13 cities and three categorized areas over 2004–2013 are obtained, which are listed in Table 4. As shown in Table 4, the average APICE of four cities is over 0.3 during our study period. Specifically, Xuzhou has the largest abatement potential, which almost reaches 0.6, followed by Zhenjiang, Lianyungang and Huaian. Nanjing, Suzhou, Wuxi, Yangzhou, Nantong, Yancheng and Suqian may reduce 10%–30% of their actual industrial CO_2 emissions in their production process, while Changzhou and Taizhou have the lower abatement potential, which is close to zero. At the area level, Subei has the highest abatement potential, which nearly reaches 0.5. Sunan has the second highest potential, and Suzhong has the lowest abatement potential about 0.15. On the whole, the average APICE of the Jiangsu Province is 0.282, which means that over a quarter of Jiangsu's ICE is excessive emission.

As shown in Table 4, Jiangsu's average annual industrial CO_2 emission reductions can attain 15,654.00 (ten thousand tons), accounting for 28.2% of average annual actual emissions. In terms of abatement amount, Xuzhou, Suzhou and Zhenjiang all account for over 10% of total potential emission reductions. Specifically, Xuzhou has the highest potential emission reductions of 5540.05 (ten thousand tons) and the highest abatement contribution of 35.39%, followed by Suzhou and Zhenjiang.

While Nanjing, Wuxi, Changzhou, Yangzhou, Nantong, Yancheng, Huaian and Lianyungang account for 1%–10% of the total potential emission reductions. Suqian and Taizhou account for less than 1%, meaning that they have little effect on the total potential emission reductions. It should be noted that abatement contribution is not fully consistent with abatement potential due to regional variation in actual industrial CO_2 emissions. For instance, the APICE of Suqian is 0.273, ranking as no. 5, but its abatement contribution is the least. On the other hand, abatement contribution largely varies in different areas. Subei and Sunan can actually affect the total reductions by 45.78% and 44.95%, much higher than 9.26% in Suzhong.

Table 4. Average industrial abatement potential of regions in Jiangsu over 2004–2013.

Region	Abatement Potential	R_1	Average Annual Actual Emission (10^4 tons)	Potential Emission Reduction (10^4 tons)	Abatement Contribution	R_2
NJ	0.191	9	5691.17	1085.87	6.94%	5
SZ	0.197	7	11,637.25	2291.37	14.64%	2
WX	0.192	8	6770.49	1302.64	8.32%	4
CZ	0.093	12	2919.47	271.22	1.73%	10
ZJ	0.511	2	4078.71	2085.85	13.32%	3
YZ	0.152	10	3189.58	485.13	3.10%	9
TZ	0.061	13	2020.65	123.06	0.79%	12
NT	0.212	6	3978.74	841.90	5.38%	6
YC	0.109	11	1812.20	197.53	1.26%	11
HA	0.394	4	2040.33	804.70	5.14%	7
SQ	0.273	5	411.17	112.04	0.72%	13
XZ	0.572	1	9688.79	5540.05	35.39%	1
LYG	0.429	3	1194.37	512.62	3.27%	8
Sunan	0.226		31,097.09	7036.96	44.95%	
Suzhong	0.158		9188.97	1450.09	9.26%	
Subei	0.473		15,146.85	7166.95	45.78%	
Jiangsu	0.282		55,432.91	15,654.00	100.00%	

Note: R_1—the rank of abatement potential; Abatement contribution—the proportion of potential emission reduction; R_2—the rank of abatement contribution.

As mentioned above, our industrial abatement model is based on a DEA efficiency variance estimating method, which implies that the lower the efficiency, the more redundancy of inputs and undesirable outputs in the production process, namely the larger emission reduction potential. XZ and ZJ have the highest abatement potential and contribution, whose main industries are traditional high energy consumption and high carbon emission industries of mining and selection, metallurgy, and iron and steel. Generally, these high-carbon industries have lower carbon efficiency than other industries. Subsequently, industrial structure dominated by high-carbon industries makes carbon efficiency of the two cities lower than that of other neighboring regions. In addition, their actual carbon emissions are relatively large as well. Therefore, abatement potential and contribution in XZ and ZJ are much higher than other regions.

4. Conclusions

With the SBM-Undesirable model, in this paper, we firstly studied annual industrial CO_2 emission efficiency of 13 prefecture-level cities in Jiangsu Province from 2004 to 2013. Then, we further analyzed space-time distribution and distributional evolution tendency of TFICEE during our study period, by using GIS visualization method and kernel density estimation, respectively. In addition, based on industrial abatement model, we worked out average annual industrial abatement potential and potential emission reductions of various regions in Jiangsu Province.

The empirical results show that TFICEE of most cities and areas has different degrees of improvement with the economy development, and Jiangsu's TFICEE levels showed an upward trend on the whole during our study period. Additionally, there exists a significant spatial inequality of TFICEE across various regions in Jiangsu, but the regional disparity has been narrowing over time. By examining regional industrial abatement potential and potential emission reductions, we find that Subei has the highest abatement potential, which is nearly up to 0.5, and makes the greatest contribution to the total potential emission reductions, which is more than 45%. In particular, Xuzhou, a city of Subei, has the highest abatement potential and potential emission reductions among 13 cities, which are more than 0.5 and 35%, respectively. On the whole, Jiangsu's industrial average annual CO_2 emission reductions can attain 15,654.00 (ten thousand tons), accounting for 28.2% of average actual annual emissions.

As mentioned above, there exists significant regional inequality of abatement potential, economic development and industrial structure in Jiangsu Province, which are crucial for the development and implement of abatement policy. Therefore, in order to formulate the most suitable emission reduction policy, local municipal government should take all these factors into consideration. From the results of this study, Sunan and Subei have relatively large emission reduction potential and should step up efforts to reduce emissions. Nevertheless, due to differences in economic development, the specific policies are different. In light of the high level of economic development and industrial technology, Sunan should vigorously develop the technology-intensive industries to realize the transformation of industrial structure. However, limited to the stage of industrial development, Subei should increase the investment on upgrade technology and equipment level, promote cross-regional mergers and acquisitions, and raise the level of industry concentration to form scale effect. XZ and ZJ, having the largest abatement potential and contribution, especially should not only actively promote technological innovation and adjust the industrial structure dominated by high-carbon industries, but also carry out inter-regional cooperation to upgrade and integrate the industrial scale efficiency. On the other hand, the Jiangsu provincial government should further break down inter-regional market barriers to promote the flow of technologies, capitals and talents within the entire province. In addition, it is vital to establish the internal dynamic mechanism of emission reduction and design incentive compatible mechanisms to coordinate regional economic development.

Of course, this study still has some limitations. It does not consider industrial carbon transfer among the regions in Jiangsu Province, which may result in inaccurate estimation of regional TFICEE. In addition, the quantitative analysis for regional disparity on industrial carbon emission efficiency and abatement potential is our future research focus.

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Abbreviations

The following abbreviations are used in this manuscript:

ICE	Industrial CO_2 Emission
TICE	Target Industrial CO_2 Emission
LICE	Loss Industrial CO_2 Emission
TFICEE	Industrial CO_2 Emission Efficiency under Total Factor Frame
APICE	Abatement Potential of Industrial CO_2 Emission
NCV	Net Caloric Value
CEF	CO_2 Emission Factor
COF	CO_2 Oxidation Factor

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