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Multi-directional efficiency analysis-based regional industrial environmental performance evaluation of China

Ke Wang* • Shiwei Yu • Mo-Jie Li • Yi-Ming Wei

Abstract This study evaluates the environmental efficiency of industrial sectors of Chinese major cities. The Multi-directional efficiency analysis (MEA) approach are utilized for evaluation, thus both the integrated MEA efficiency levels and the efficiency patterns, which are represented by the variable specific MEA efficiency according to each type of the industrial pollutant emission or discharge, of Chinese major city are detected. In addition the industrial energy conservation and pollutant reduction potentials are measured and the relationship between environmental pressure and income are explored at the regional level of China. The main findings include: (i) The MEA environmental efficiency increases of the economic less developed cities were faster than the cities in the well-developed region, which indicates that the inequitable nationwide industrial developments of Chinese cities have started to alleviate. (ii) Although some Chinese cities show similar environmental efficiency levels, the undesirable output variable specific efficiency patterns of these cities are diversified, and according to the variable specific efficiency, the most possible efficiency increase potential of each Chinese major city can be identified. (iii) An N-shaped Environmental Kuznets Curve exists in the industrial sectors of Chinese major cities. (iv) Different Chinese cities should have different industrial pollutant reduction priorities, which east China cities should pay more attention on their industrial waste gas emissions and industrial waste water discharges, while west China cities should mainly focus on their industrial soot and dust emissions, and solid waste discharges.

Keywords Environmental performance • Industrial sector • Pollutant reduction potential • Multi-directional Efficiency Analysis (MEA)

1 Introduction

The industrial sector is the largest energy consumer and the largest pollutant emitter in China, which consumes up to 60% of total energy consumption of China and produces more than half of the major pollutants in China. In addition, most of the industrial enterprises are concentrated in large Chinese cities. In the latest 30 years, China has experienced an extremely rapid growth in its economy and overtook Japan as the second largest economy in the world since 2011. However, the rapid economic growth was associated with substantially increase in primary energy consumption, and has led to serious environmental problems because of the rapid increase in pollutants (e.g., industrial waste gas, waste water and solid wastes) production and emission or discharge (Wei et al. 2009; Wei et al. 2010; Wang et al. 2013). Nowadays, China has overtaken the US and became the largest energy consumer and carbon emitter in the world since 2010 and 2007, respectively (EIA 2013; CDIAC 2013).

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According to the recently issued report by Yale University and Columbia University, the 2012 Environmental Performance Index (EPI), China got the rank of 116 among all 132 under evaluated countries and territories on its environmental performance (World Bank 2007). In this report, the measurements of fossil fuel combustion and related air and water pollutions are the major contributions in the EPI calculation. Furthermore, the World Bank report indicated that the combined health and non-health loss caused by outdoor air pollution and water pollution for China accounted up to approximately 100 billion US$, which was about 5.8% of China's GDP per year (Emerson 2012). The air pollution in large China's cities has led to higher incidences of lung cancer and respiratory system problems. The water pollution has caused growing levels of diarrhea and cancer in urban and rural areas in China. And the water pollution has exacerbated China's severe water scarcity problems and brought the overall loss to approximately 1% of China's annual GDP. The China Energy Report 2012 issued by the Center for Energy & Environmental Policy Research (CEEP) also pointed out that the industrial soot and dust emissions in Chinese major cities have caused more than 20 billion US$ loss and approximately 65,000 death cases in 2007 (Wei et al 2012). Therefore, the industrial environmental problem is threatening the sustainable development of China.

During the 11th (2006-2010) and 12th (2011-2015) Five Year Plan, the Chinese government has put forward a series policies and laws on environment protection and energy conservation, so as to realize sustainable development and construct an environment-friendly and resource-saving society. One of Chinese highest priority policies and strategic targets on environmental protection is the energy intensity (energy consumption per unit of GDP) reduction and the total discharge of major pollutants (SO_2, NO_x, and COD etc.) reduction target, in which, the energy intensity is required to respectively reduce by 20% and 16%, and the pollutants discharge needed to respectively reduce by 10% and 8% during 2006-2010 and 2011-2015 at the Chinese national level. In order to realize these environment protection targets, a series of energy and environmental policies and regulations were proposed and implemented at the regional level of Chinese provinces and cities so as to support the central and local governments' efforts on industrial energy consumption related water and air pollution control as well as solid waste disposal. In addition, because the economic growth modes and industrial structures, as well as the energy consumption structures and natural resources endowments of different Chinese regions vary a lot, the environment protection policies and strategies of different Chinese regions are various, the industrial environmental performances of China may also vary significantly across different Chinese cities. Therefore, it will be necessary to evaluate the industrial environmental efficiency at the city level of China, and the evaluation results will be valuable for understanding the current environmental performance, identifying the environmental efficiency promotion potential and pollutant reduction potential of China, and thus, providing appropriate policy implication in China's further effort on environment protection and sustainable development.

The aim of this study is to evaluate the industrial environment efficiency of China's major cities during the period of 2006-2010, and identify the energy conservation and pollutants reduction potentials of the industrial sectors of Chinese major cities. In addition, the relationship between Chinese economic development and the regional environmental performance will be analyzed, and the policy implication will be discussed.

The remainder of this paper is laid out as follows. In the next section, a brief overview on China's regional environmental efficiency evaluation is given and the reason of choosing the multi-directional efficiency analysis (MEA) approach in this study is interpreted. Section 3 presents the MEA method and proposes the efficiency measures. The next section then discusses the data and variables utilized for environmental efficiency evaluation. Section 5 to 7 respectively presents and discusses China's regional industrial environmental efficiency level and pattern, the relationship between environmental efficiency and economic development in China, and the environmental efficiency increase potential, as well as the pollutants reduction potentials of Chinese major cities. Section 8 concludes this paper.

2 Frontier techniques based environmental efficiency evaluation in China

To date, quite a few studies on Chinese regional environmental efficiency using the frontier based approach have been published in academic journals. For example, Zhang et al. (2008) conducted an ecological efficiency analysis for China's regional industrial systems by utilizing a Data Envelopment Analysis (DEA) based method. Their empirical results shown that, the provinces with higher level of GDP per capita will have higher ecological efficiency relatively, but with a few exceptions of Chinese west provinces. Hua et al. (2007) estimated the ecological (environment) efficiency of the pulp and paper industry along Chinese Huaihe River based on a DEA model and the undesirable output of biochemical oxygen demand (BOD) and the non-discretionary input (pollutant emission quota) are modeled simultaneously. Zhou et al. (2013) evaluated the environmental efficiency of Chinese power industry at the provincial level through a combined model of non-radial Slacks Based Measure (SBM) model and Tobit regression analysis. Their evaluation results indicated that three factors (power plant's innovation ability, electricity generation proportion from coal-fired plant, and power plant's generation capacity) have positive effect on environmental efficiency, but two factors of rate on waste discharge fee and pollutant treatment investment are negatively related to environmental efficiency. Yang et al. (2012) explored the spatial-temporal differentiation of industrial ecological efficiency in China by utilizing the DEA model and Exploratory Spatial Data Analysis (ESDA) model and indicated that the provinces with higher efficiency levels are concentrated in the eastern China, and the low efficiency provinces are mainly located in the western and central China. In addition, this spatial relationship of industrial ecological efficiency between different Chinese provinces just slightly changed in the last three decades. Zhu et al. (2011) investigated the eco-efficiency of Chinese provinces based on non-redial DEA approach and their efficiency estimation results shown that the less developed western part of China suffered the worst eco-efficiency which may cause great environment risk, and the provinces in this area were facing the poor economic and bad environmental condition simultaneously. Bi et al. (2012) also applied a SBM model to measure the industrial environmental performance of Chinese provinces. Their evaluation results indicated that the waste gas and solid waste from industrial sectors have more impact on China's regional environmental efficiency, and the west region of China performed better in both economy and environmental control compared with other areas. Zhang (2009) employed a traditional DEA framework to evaluate the environmental efficiency of Chinese industrial sectors and pointed out there was an about 60% reduction potential on air pollution in the whole China. Similar environmental performance evaluation in China would be found in (Li et al. 2013; Zhou et al. 2013; Song et al. 2012; Song et al. 2013; Yang and Wang 2013).

It could be noticed that, the empirical results and conclusions of the above mentioned studies are varied or even opposite, especially concerning the environmental efficiency levels and pollutants reduction potentials of different Chinese regions. In addition, most of the above studies on Chinese regional environmental efficiency are based on the traditional radial DEA or non-radial SBM models. Under the radial DEA model, the Decision Making Units (DMUs) are restricted to the radial expansions on all desirable output variables, and the radial contractions on all input variables and undesirable output variables. However, this radial adjustment may be somewhat inappropriate in efficiency evaluation, because different input or output variables may adjust with diversified proportions in order to get more appropriate and specific efficiency measures. Under the non-radial SBM model, the undesirable output variables are treated as freely and strongly disposable inputs, which may not satisfy the jointness assumption on desirable and undesirable outputs: any decrease in undesirable outputs must implies a decrease in desirable outputs simultaneously for efficient DMUs. Therefore, the methods utilized in above studies have been criticized by many studies (Murty et al. 2012; Färe et al. 2001; Färe et al. 2004; Leleu 2013).

In this paper, we aim to investigate Chinese regional industrial environmental performance at the city level in greater depth through measuring not just the efficiency level and its variance trend, but also identifying the efficiency pattern and estimating the pollutant reduction potential of 30 Chinese major cities. To realize this research objective, the application of the multi-directional efficiency analysis (MEA) approach (Bogetoft and Hougaard 1998), instead of the DEA approach, will be necessary, since MEA approach can identify both efficiency status and efficiency patterns of industrial sector in each Chinese major city.

The MEA approach is considered an alternative of the DEA approach, in which the input reduction and output expansion benchmarks are selected proportionally to the potential improvement on efficiency, and the efficiency is identified by considering the improvement potential separately in each input variable and output variable. In addition, all the adjustments on input, desirable and undesirable output variables are further constrained in a united optimization when calculating the integrated MEA efficiency, thus, the jointness of desirable and undesirable outputs is satisfied and explicitly modeled. Therefore, the MEA approach is more appropriate for estimating the integrated environmental efficiency and investigating the efficiency patterns, i.e., the specific pollutant emission or discharge efficiency, of the industrial sector of each Chinese city. In addition, since MEA considers the improvement potential in each variable separately, it is suitable in the evaluation situations that the aim of each DMU is to simultaneously reduce the utilization of some inputs and increase the production of some outputs, without presetting the priorities on improvements of some variables over other variables.

Although the MEA approach has been successfully applied in several field such as banking, agriculture, transportation, and health care (Asmild and Pastor 2010; Asmild and Matthews 2012; Holvad et al. 2004; Asmild et al. 2003; Asmild et al. 2009), few study has utilized this approach in energy and environmental performance evaluation in China (Wang et al. 2013), and to our knowledge, no study on regional environmental efficiency evaluation of industrial sectors in China at the city level has applied this approach. In this study, we utilize the MEA method to investigate both the levels and the patterns of industrial environmental efficiency of Chinese major cities, and try to get additional insights into the characteristics of regional environmental performance and provided more appropriate and specific policy implications on China’s regional environmental management.

3 Methodology: multi-directional efficiency analysis (MEA)

The MEA is utilized instead of the traditional radial DEA approach in this study, which could help us have a deeper insight into the regional environmental efficiency of industrial sectors in Chinese major cities by investigating not just the efficiency status of each city but also identifying the efficiency patterns in each city. Because the MEA method specifies a group of efficiency measures relative to a group of benchmarks indicated by the improvement potential associated with each of the input and output variables, the efficiency measure under MEA is not restricted to the radial expansions of desirable outputs, radial contractions of inputs and radial contractions of undesirable outputs. Thus, both the undesirable output variable specific efficiency can be detected and the integrated environmental efficiency can be measured through MEA.

In this study we consider there are *n* Chinese cities in the data set observed in each study period *t*. The *j*th city at period *t* utilizes *m* inputs of x_{ij}^t, i=1,…,*m*, (such as energy, labor and capital) to produces *s* desirable outputs of g_{rj}^t, r=1,…,*s*, (like GDP or industrial value added) and *h* undesirable outputs of b_{fj}^t as byproduct (e.g., SO_2 and NO_x emissions, waste water and solid waste). In order to find the ideal reference point for a specific observation or city $(x_{i0}^t, g_{r0}^t, b_{f0}^t)$, we first solve the following Models (1) and (2) for each of the discretionary input, desirable and undesirable output, respectively. As we mainly concern the reduction potentials for the energy input, desirable output, and undesirable / pollution outputs whilst keeping the other input variables (labor and capital stock) fixed for each Chinese city, both the input oriented and output oriented MEA model are utilized, and the energy input and all desirable and undesirable outputs are considered as the discretionary variables, while the labor and capital stock inputs are treated as non-discretionary variables.

$$
\begin{aligned}
&\min d_{i0}^t \quad or \quad d_{f0}^t \\
&s.t. \ \sum\nolimits_{j=1}^n \lambda_j x_{ij}^t \le d_{i0}^t, \\
&\quad \sum\nolimits_{j=1}^n \lambda_j x_{-ij}^t \le x_{-i0}^t, -i = 1,\ldots,i-1,i+1,\ldots,k, \\
&\quad \sum\nolimits_{j=1}^n \lambda_j x_{ij}^t \le x_{i0}^t, i = k+1,\ldots,m, \\
&\quad \sum\nolimits_{j=1}^n \lambda_j b_{fj}^t \le d_{f0}^t, \\
&\quad \sum\nolimits_{j=1}^n \lambda_j b_{-fj}^t \le x_{-f0}^t, -f = 1,\ldots,f-1,f+1,\ldots,h, \\
&\quad \sum\nolimits_{j=1}^n \lambda_j g_{rj}^t \ge g_{r0}^t, r = 1,\ldots,s, \\
&\quad \lambda_j \ge 0, j = 1,\ldots,n.
\end{aligned} \tag{1}
$$

$$
\begin{aligned}
&\max d_{r0}^t \\
&s.t. \ \sum\nolimits_j \lambda_j g_{rj}^t \ge d_{r0}^t, \\
&\quad \sum\nolimits_j \lambda_j g_{-rj}^t \ge g_{-r0}^t, -r = 1,\ldots,r-1,r+1,\ldots,s, \\
&\quad \sum\nolimits_j \lambda_j x_{ij}^t \le x_{i0}^t, i = 1,\ldots,m, \\
&\quad \sum\nolimits_j \lambda_j b_{fj}^t \le b_{f0}^t, f = 1,\ldots,h, \\
&\quad \lambda_j \ge 0, j = 1,\ldots,n.
\end{aligned} \tag{2}
$$

In Model (1), the first *k* inputs (x_{ij}^t, i=1,…,*k*) are discretionary inputs and the remaining *m-k* inputs (x_{ij}^t, i=*k*+1,…,*m*) are non-discretionary inputs. Subscript –*i* denotes all input dimensions except the *i*th dimension, and subscript –*f* denotes all undesirable dimensions except the *f*th dimension. Similarly, in Model (2), subscript –*r* denotes all desirable dimensions except the *r*th dimension. λ_j is the intensity variable associated with each city to connect the input and output variables. d_{i0}^t, d_{f0}^t and d_{r0}^t are the target values for the *i*th input reduction, the *f*th undesirable output reduction and the rth desirable output expansion. By solving Models (1) and (2), the ideal reference point for $(x_{i0}^t, g_{r0}^t, b_{f0}^t)$ could be obtained at $(d_{i0}^{t*}, d_{r0}^{t*}, d_{f0}^{t*})$, where * denotes the optimal solutions. Then, we consider the following Model (3).

$$
\begin{aligned}
&\max \beta_0^t \\
&s.t.\ \sum_j \lambda_j x_{ij}^t \le x_{i0}^t - \beta_0^t (x_{i0}^t - d_{i0}^{t*}), i = 1,...,k, \\
&\quad \sum_j \lambda_j x_{ij}^t \le x_{i0}^t, i = k+1,...m, \\
&\quad \sum_j \lambda_j b_{fj}^t \le b_{f0}^t - \beta_0^t (b_{f0}^t - d_{f0}^{t*}),\ f = 1,...,h, \qquad (3) \\
&\quad \sum_j \lambda_j g_{rj}^t \ge g_{r0}^t + \beta_0^t (d_{r0}^{t*} - g_{r0}^t), r = 1,...,s, \\
&\quad \lambda_j \ge 0,\ j = 1,...,n.
\end{aligned}
$$

The variables and parameters used in Model (3) have the same definitions as in Models (1) and (2). β_0^t is the MEA efficiency measure. The optimal solution of Model (3) is $(\lambda_j^*, \beta_0^{t*})$, and the relative variable specific MEA efficiencies for the city of $(x_{i0}^t, g_{r0}^t, b_{f0}^t)$ can be defined as follows.

$$
\left(\theta_i^t, \theta_r^t, \theta_f^t\right) = \left(\frac{x_{i0}^t - \beta_0^{t*}(x_{i0}^t - d_{i0}^{t*})}{x_{i0}^t}, \frac{g_{r0}^t}{g_{r0}^t + \beta_0^{t*}(d_{r0}^{t*} - g_{r0}^t)}, \frac{b_{f0}^t - \beta_0^{t*}(b_{f0}^t - d_{f0}^{t*})}{b_{f0}^t} \right) \qquad (4)
$$

In addition, based on the individual variable specific efficiencies above, a single integrated measure of MEA efficiency for the city of $(x_{i0}^t, g_{r0}^t, b_{f0}^t)$ can be defined as in (5).

$$
\theta_0^t = \frac{1 - \frac{1}{m+h}\sum_{i=1}^{m} \frac{\beta_0^{t*}(x_{i0}^t - d_{i0}^{t*})}{x_{i0}^t} - \frac{1}{m+h}\sum_{i=1}^{h} \frac{\beta_0^{t*}(b_{f0}^t - d_{i0}^{t*})}{b_{f0}^t}}{1 + \frac{1}{s}\sum_{r=1}^{s} \frac{\beta_0^{t*}(d_{r0}^{t*} - g_{r0}^t)}{g_{r0}^t}} \qquad (5)
$$

In this study, we name θ_0^t as the integrated MEA environmental efficiency, and $\theta_i^t, \theta_r^t, \theta_f^t$ as the input variable (energy consumption) specific efficiency, desirable output variable (industrial value added) specific efficiency, and undesirable output variable (pollutant emission or discharge) specific efficiency, respectively.

4 Data and variables

We evaluate the industrial environmental efficiency of Chinese 30 major cities in this study. All these 30 cities are the capital cities of Chinese provinces, autonomous regions and municipalities. Lasa, Taibei, HongKong and Macao are not included because of data absence. The evaluation period is from 2006 to 2010 (the 11th Five Year Plan period). Three inputs, one desirable output and five undesirable outputs are included in our study framework. Three inputs employed are (i) Energy: total energy consumption of industrial enterprises (x_1), (ii) Labor: number of employed person of industrial enterprises (x_2), and (iii) Capital: net value of fixed assets of industrial enterprises (x_3). The desirable output is value-added of industrial enterprises (g). And five undesirable outputs utilized are total volume of industrial (i) waste gas emission (b_1), (ii) soot emissions (b_2), (iii) dust emission (b_3), (iv) waste water discharge (b_4), and (v) solid waste discharge (b_5).

The data on capital, labor, and industrial value added are collected from China statistical yearbook (NBS 2007–2011a) and China city statistical yearbook (NBS 2007–2011b); the industrial energy data are obtained from China energy statistical yearbook (NBS 2007–2011c); and the pollutants data are collected from China statistical yearbook on environment (NBS 2007–2011d). The monetary data, including net value of fixed assets and value-added of industrial enterprises, are converted into 2010 constant prices of Chinese Yuan (CN￥$_{2010}$). Energy consumption of industrial enterprises includes all types of energy (e.g., coal, oil, gas and electricity), and all the energy consumption data are converted into tonnes of coal equivalent (tce). Table 1 presents the descriptive statistics of input and output data of industrial sectors of 30 Chinese major cities during 2006-2010.

Table 1 Descriptive statistics of inputs and outputs for industrial sector of Chinese major cities (2006-2010)

Input and output variables[a]	**Unit**	**Total volume**	**Mean**	**Maximum**	**Minimum**	**Std. dev.**
Value-added of Industrial Enterprises (G)	Billion ￥$_{2010}$	17666.623	117.777	610.000	7.360	113.625
Total Energy Consumption of Industrial Enterprises (I)	Million tce	2535.401	16.903	58.560	0.048	12.078
Number of Employed person of Industrial Enterprises (I)	Thousand person	90681.872	604.546	2956.300	44.100	592.855
Net value of fixed assets of Industrial Enterprises (I)	Billion ￥$_{2010}$	20861.799	139.079	807.095	9.756	148.370
Total Volume of Industrial Waste Gas Emission (B)	Billion m^3	41293.200	275.288	1296.900	1.100	254.694
Total Volume of Industrial Soot Emission (B)	Thousand tonne	5118.296	34.122	131.232	0.093	25.784
Total Volume of Industrial Dust Emission (B)	Thousand tonne	3752.645	25.018	201.087	0.000	34.868
Total Volume of Industrial Waste Water Discharge (B)	Million tonne	23341.830	155.612	864.960	4.750	188.017
Total Volume of Industrial Solid Wastes Discharge (B)	Million tonne	1334.349	8.896	28.374	0.014	7.075

[a] G, I, B indicate desirable output, input, and undesirable output, respectively.

5 Regional industrial environmental efficiency level and pattern of China

Through MEA Models (1) to (3) and definitions (4) and (5), the integrated MEA environmental efficiency and the input and output variable specific efficiency for each Chinese region can be obtained. We first consider the integrated MEA environmental efficiency scores which are listed in Table 2 and illustrated in Fig. 1.

Table 2 Integrated MEA efficiency and specific efficiency of industrial sector of Chinese major cities

Efficiency	Integrated MEA efficiency					Industrial value added efficiency					Industrial energy consumption efficiency				
	2006	2008	2010	5 year average	rank	2006	2008	2010	5 year average	rank	2006	2008	2010	5 year average	rank
Beijing	0.617	0.688	1.000	0.760	9	0.882	0.900	1.000	0.932	12	0.698	0.760	1.000	0.803	12
Tianjin	0.496	0.878	1.000	0.818	8	0.903	0.993	1.000	0.973	8	0.633	0.884	1.000	0.855	7
Shijiazhuang	0.202	0.423	0.448	0.375	24	0.743	0.894	0.908	0.872	16	0.301	0.501	0.546	0.459	26
Taiyuan	0.225	0.394	0.378	0.335	26	0.565	0.751	0.734	0.689	27	0.389	0.494	0.492	0.462	24
Huhehot	0.511	0.781	1.000	0.859	5	0.874	0.994	1.000	0.974	6	0.572	0.757	1.000	0.866	6
Shenyang	0.630	0.764	1.000	0.848	6	0.928	0.967	1.000	0.977	5	0.790	0.827	1.000	0.915	3
Changchun	0.439	0.584	1.000	0.735	11	0.797	0.880	1.000	0.927	13	0.576	0.675	1.000	0.787	13
Harbin	0.262	0.266	0.469	0.336	25	0.676	0.701	0.870	0.755	25	0.384	0.369	0.512	0.427	27
Shanghai	0.389	0.528	0.735	0.531	16	0.784	0.884	0.958	0.874	15	0.537	0.634	0.762	0.632	15
Nanjing	0.300	0.457	0.524	0.448	20	0.731	0.861	0.893	0.848	19	0.446	0.568	0.620	0.555	20
Hangzhou	0.375	0.429	0.458	0.440	21	0.779	0.828	0.849	0.832	22	0.532	0.573	0.619	0.590	19
Hefei	0.640	1.000	1.000	0.928	1	0.952	1.000	1.000	0.990	2	0.749	1.000	0.999	0.950	2
Fuzhou	0.696	0.697	0.819	0.746	10	0.966	0.949	0.985	0.968	9	0.786	0.805	0.846	0.810	11
Nanchang	0.533	0.699	0.765	0.714	12	0.900	0.958	0.982	0.952	10	0.679	0.823	0.934	0.829	10
Jinan	0.598	1.000	1.000	0.865	3	0.948	1.000	1.000	0.986	3	0.646	1.000	1.000	0.875	5
Zhengzhou	0.313	0.481	0.511	0.431	22	0.861	0.906	0.907	0.892	14	0.389	0.570	0.639	0.519	23
Wuhan	0.303	0.391	1.000	0.536	15	0.734	0.795	1.000	0.851	18	0.423	0.503	1.000	0.606	17
Changsha	0.525	1.000	1.000	0.879	2	0.888	1.000	1.000	0.973	7	0.600	1.000	1.000	0.898	4
Guangzhou	0.578	0.811	1.000	0.823	7	0.916	0.987	1.000	0.978	4	0.637	0.856	1.000	0.845	8
Nanning	0.278	0.443	0.593	0.551	14	0.745	0.854	0.923	0.870	17	0.463	0.606	0.796	0.697	14
Haikou	0.833	0.833	0.820	0.864	4	1.000	1.000	0.999	1.000	1	1.000	1.000	1.000	1.000	1
Chongqing	0.164	0.316	0.414	0.293	27	0.539	0.751	0.807	0.700	26	0.337	0.480	0.583	0.461	25
Chengdu	0.508	0.800	0.696	0.671	13	0.862	0.992	0.966	0.944	11	0.671	0.962	0.872	0.844	9
Guiyang	0.175	0.218	0.299	0.227	30	0.593	0.552	0.651	0.606	29	0.311	0.396	0.461	0.381	29
Kunming	0.313	0.428	0.654	0.468	18	0.749	0.815	0.947	0.843	20	0.428	0.527	0.651	0.533	21
Xian	0.353	0.457	0.511	0.450	19	0.728	0.844	0.883	0.829	23	0.562	0.629	0.683	0.630	16
Lanzhou	0.159	0.227	0.370	0.251	28	0.477	0.545	0.710	0.583	30	0.331	0.410	0.506	0.414	28
Xining	0.152	0.259	0.264	0.236	29	0.506	0.705	0.736	0.663	28	0.319	0.389	0.386	0.374	30
Yinchuan	0.278	0.406	0.618	0.418	23	0.651	0.794	0.944	0.789	24	0.445	0.514	0.647	0.527	22
Urumqi	0.348	0.316	0.716	0.508	17	0.749	0.702	0.954	0.833	21	0.474	0.455	0.760	0.596	18

Fig. 1 shows that the average integrated MEA environmental efficiencies of Chinese cities and the cities in all three areas (east, central and west China) all experienced an obvious increase during the 11th Five Year Plan period, and the efficiency scores of the east, central and west areas have same increase trend which significantly increased from 2006 to 2007, slightly reduced in 2008, and then continuously improved from 2009. In general, the integrated MEA environmental efficiency of the industrial sectors of Chinese cities increased more than 72% during 2006-2010 which indicates that the energy and environmental policies and regulations proposed and implemented by the Chinese government within the 11th Five Year Period have begun to play a role in increasing the industrial environmental performance of Chinese major cities. According to the average integrated MEA efficiency, east China cities enjoyed the highest industrial environmental efficiency, but cities in west China suffered the lowest efficiency, which indicates that the economically well developed and technologically advanced regions will also enjoy high environmental performances. Although the environmental performances of central and west China cities were comparatively lower, their increase speeds were higher, since the coefficient of variation (CV) of integrated MEA efficiency of all 30 Chinese cities decreased from 0.45 to 0.36 during this period. This result indicates that, in general, the cities with lower initial MEA efficiency scores will also improve faster on their environmental performance, which will have a positive effect on narrowing the performance gaps between the well-developed regions and the undeveloped regions of China and mitigating the inequitable nationwide development of Chinese cities. According to the ranks of the 5 year average MEA efficiency of 30 Chinese cities (shown in the sixth column of Table 2), the industrial sectors of Hefei has the best environmental performance (average MEA efficiency score is 0.928), followed by Changsha (0.879), Jinan (0.865), Haikou (0.864), and Huhehot (0.859). On the contrary, the industrial environmental performance of Guiyang (0.227) was worst, followed by Xining (0.236), Lanzhou (0.251), Chongqing (0.293), and Taiyuan (0.335). The largest MEA environmental efficiency gaps between the best performed and the worst performed Chinese cities were approximately 0.70.

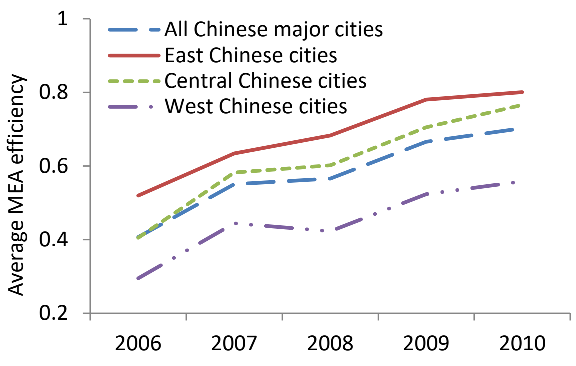

Fig. 1 Integrated MEA efficiency change of Chinese major cities (2006-2010)

In order to further examine the MEA efficiency changes, now, we focus on the ranking changes of Chinese cities in 2010 compared with 2006. The mean rank for east China cities decreased by about 2 places, while the mean ranks for central China and west China cities respectively increased by 2 and 1 places. Overall, the greatest improvement happened in Wuhan whose rank moved up 19 places from 20th place in 2006 to 1st place (tied with other cities) in 2010. However, least improved cities fell 10 places: Fuzhou fell from 2nd place in 2006 to 12th place in 2010, and Haikou fell from 1st place (tied with other cities) in 2006 to 11th place in 2010. In general, there are eleven cities experienced significant rank changes that over 5 places. There are just two cities (Shanghai and Xining) showing no rank changes. The rank of Shanghai kept on 14th place in 2006 and 2010, and that of Xining was sucked in 30th place all the time. The above results reinforced the conclusion that the MEA efficiency increases of less developed central and west China cities were faster than those of the east China cities, and thus the inequitable nationwide industrial developments of east, central and west Chinese cities have started to mitigate during 2006-2010 from the perspective of integrated MEA environmental efficiency evaluation.

The MEA efficiency rankings were further clustered into seven groups according to the levels of rank changes, which are illustrated in Fig. 2, so as to provide a better understanding of MEA efficiency changes during 2006-2010. We name the groups as G1 to G7 from right to left as shown below the horizontal axis in Fig. 2. G1 contains the most significant ranking increase cities while G7 contains the most significant ranking decrease cities. The cities belong to G4 show no ranking changes. If a city locates in G1-3, its integrated MEA environmental efficiency has improved relatively to other cities in this study period, and if a city locates in G5-7, the situation is reverse.

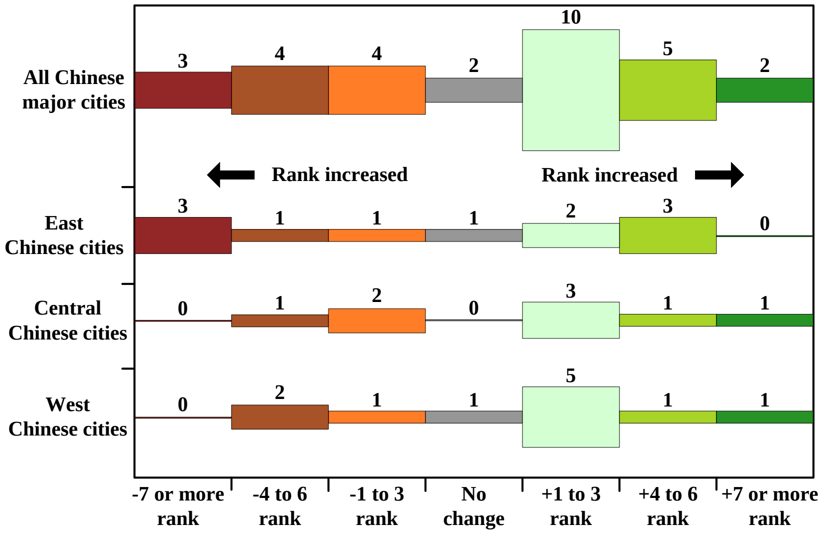

Fig. 2 Rank changes of integrated MEA efficiency of Chinese major cities (2006-2010)

For all 30 Chinese major cities, about 57% cities increased ranks, which imply relative MEA efficiency increase, and about 37% cities decreased ranks, which demote relative MEA efficiency decrease. The remaining 6% cities evidence no relative MEA efficiency change. For the east China cities, the distribution of rank changes is evenly divided as 45% increased, 45% decreased, and 10% remained in the same place. Rank changes for the central China cities are as follows: 63% cities relatively increased their MEA efficiency while 37% cities relatively decreased their MEA efficiency. For the west China cities, 64% have relative efficiency increases, 27% have relative efficiency decreases, and 9% exhibits no relative efficiency change. The most evident rank changes are 1-3 place promotion that happened in ten cities, in which five are from west China, and the second evident rank changes are 4-6 place promotion for another five cities, and three of them are east China cities. Oppositely, there are also four cities exhibit evident place deteriorations for -1 to -3 and -4 to -6, and two cities are from central China in the former and another two cities are from west China in the latter. In addition, three east China cities experienced the most obvious -7 or more than -7 place deteriorations. The above results indicate that the west China cities are the main contributors for China's integrated MEA environmental efficiency relative promotion during 2006-2010 and the relative MEA efficiency decrease cities evenly distributed in China's east, central and west areas.

Since the integrated MEA efficiency can be decomposed into the input and output variables specific efficiencies, Fig. 3 illustrates the quartile boxplots of the integrated MEA efficiency score (MEAE), the industrial value added efficiency score (IVAE), the industrial energy consumption efficiency score (ENEE), and the industrial waste gas emissions efficiency score (WGEE), which represents the other four undesirable output variable specific efficiencies as an environmental pressure, of all Chinese major cities and the cities in east, central and west China, respectively. These efficiency scores are additionally reported in Tables 2 and 3. Fig. 3 shows that, the mediums of east China cities are the highest for all the above four efficiency scores, followed by the efficiency score mediums of the central China cities, and those of the west China cities are the lowest. For all 30 Chinese major cities, the variance of IVAE is the smallest and that of MEAE is the largest. The variances of MEAE and IVAE of east China cities are smaller than those of central and west China cities. However, there are no significant differences on variances of ENEE and WGEE among the east, central and west China cities. These results imply that, in general, the MEA environmental efficiency of industrial sectors of the east China cities are both higher and more concentrated than those of the central China cities, but the MEA environmental efficiency of industrial sectors of the west China cities are both the lowest and the most divergent. In addition, the difference on MEA efficiency level among three Chinese areas are evenly contributed by the differences on IVAE, ENEE and WGEE levels among three Chinese areas, but the difference on MEA efficiency variance among three Chinese areas are mainly caused by the difference on IVAE efficiency variance among three Chinese areas.

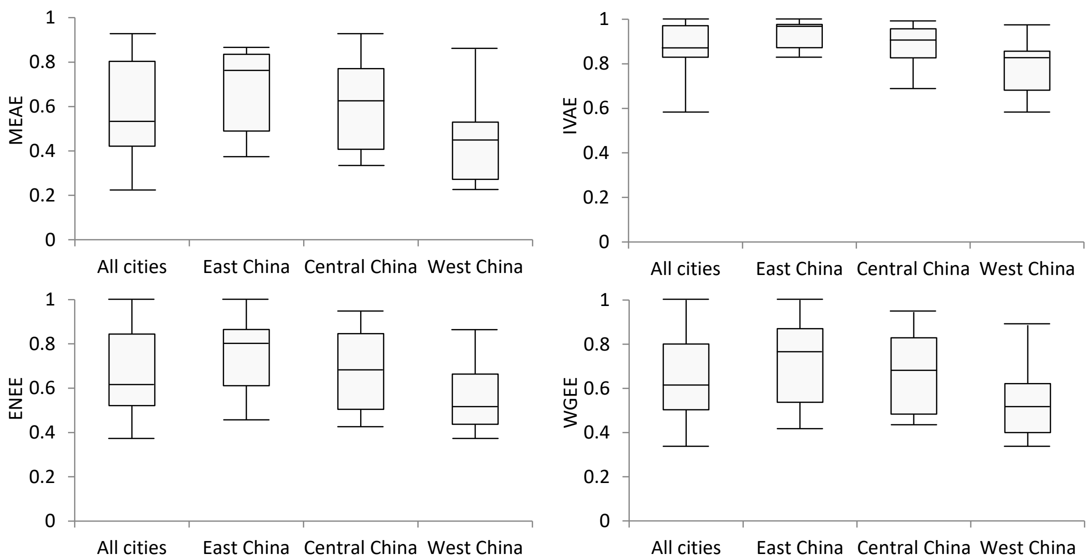

Fig. 3 Industrial MEA efficiency and specific efficiency comparison of Chinese major cities

Table 3 Undesirable output specific efficiency of industrial sector of Chinese major cities in selected years

Efficiency	Industrial waste gas emission efficiency				Industrial soot emission efficiency				Industrial dust emission efficiency				Industrial waste water discharge efficiency				Industrial solid wastes discharge efficiency			
	2006	2010	5 year average	rank	2006	2010	5 year average	rank	2006	2010	5 year average	rank	2006	2010	5 year average	rank	2006	2010	5 year average	rank
Beijing	0.665	1.000	0.763	10	0.688	1.000	0.840	6	0.643	1.000	0.771	9	0.832	1.000	0.902	5	0.666	1.000	0.785	9
Tianjin	0.518	1.000	0.805	8	0.496	1.000	0.825	7	0.498	1.000	0.825	6	0.591	1.000	0.837	11	0.563	1.000	0.861	6
Shijiazhuang	0.258	0.491	0.418	26	0.254	0.503	0.427	25	0.241	0.436	0.388	25	0.303	0.502	0.430	28	0.272	0.483	0.419	25
Taiyuan	0.369	0.463	0.437	24	0.361	0.480	0.442	24	0.355	0.452	0.424	23	0.559	0.749	0.698	14	0.357	0.451	0.425	24
Huhehot	0.610	1.000	0.887	6	0.542	1.000	0.860	5	0.498	1.000	0.871	3	0.728	1.000	0.897	6	0.560	1.000	0.864	5
Shenyang	0.749	1.000	0.888	5	0.567	1.000	0.789	9	0.572	1.000	0.820	7	0.705	1.000	0.881	7	0.691	1.000	0.892	4
Changchun	0.542	1.000	0.791	9	0.491	1.000	0.739	11	0.485	1.000	0.733	11	0.690	1.000	0.842	10	0.518	1.000	0.784	10
Harbin	0.383	0.547	0.435	25	0.343	0.504	0.391	27	0.338	0.485	0.381	27	0.535	0.728	0.621	17	0.344	0.462	0.384	28
Shanghai	0.463	0.686	0.550	17	0.477	0.782	0.588	16	0.425	0.724	0.526	17	0.628	0.902	0.765	12	0.443	0.749	0.547	17
Nanjing	0.415	0.563	0.514	22	0.407	0.679	0.586	17	0.382	0.522	0.470	22	0.418	0.567	0.507	26	0.395	0.571	0.507	21
Hangzhou	0.483	0.530	0.524	19	0.469	0.524	0.514	21	0.445	0.489	0.481	21	0.471	0.522	0.510	25	0.491	0.548	0.546	18
Hefei	0.724	1.000	0.945	3	0.601	1.000	0.920	2	0.663	1.000	0.933	2	0.600	1.000	0.920	3	0.694	1.000	0.939	2
Fuzhou	0.769	0.721	0.742	12	0.527	0.942	0.742	10	0.823	0.766	0.740	10	0.818	0.955	0.859	8	0.599	0.760	0.728	12
Nanchang	0.636	0.727	0.754	11	0.524	0.872	0.728	12	0.516	0.681	0.674	12	0.552	0.719	0.702	13	0.644	0.739	0.777	11
Jinan	0.595	1.000	0.853	7	0.685	1.000	0.909	3	0.576	1.000	0.854	5	0.720	1.000	0.906	4	0.563	1.000	0.849	7
Zhengzhou	0.385	0.560	0.500	23	0.323	0.552	0.450	23	0.314	0.460	0.412	24	0.421	0.599	0.532	22	0.352	0.566	0.476	23
Wuhan	0.421	1.000	0.604	16	0.404	1.000	0.621	14	0.389	1.000	0.591	14	0.441	1.000	0.612	18	0.398	1.000	0.613	15
Changsha	0.762	1.000	0.946	2	0.522	1.000	0.866	4	0.470	1.000	0.855	4	0.629	1.000	0.920	2	0.564	1.000	0.893	3
Guangzhou	0.625	1.000	0.892	4	0.606	1.000	0.800	8	0.554	0.997	0.796	8	0.737	1.000	0.857	9	0.628	1.000	0.840	8
Nanning	0.368	0.666	0.621	15	0.345	0.585	0.584	18	0.342	0.577	0.579	15	0.361	0.602	0.598	19	0.357	0.627	0.602	16
Haikou	1.000	1.000	1.000	1	1.000	0.968	0.994	1	1.000	1.000	1.200	1	1.000	1.000	1.000	1	1.000	0.952	0.990	1
Chongqing	0.302	0.494	0.399	28	0.294	0.489	0.391	28	0.289	0.471	0.378	28	0.307	0.546	0.420	29	0.294	0.492	0.394	27
Chengdu	0.608	0.704	0.707	13	0.557	0.637	0.648	13	0.546	0.620	0.656	13	0.573	0.751	0.673	15	0.582	0.741	0.715	13
Guiyang	0.282	0.431	0.350	29	0.272	0.428	0.345	29	0.265	0.413	0.334	29	0.373	0.611	0.496	27	0.269	0.416	0.337	30
Kunming	0.405	0.635	0.515	21	0.410	0.835	0.609	15	0.383	0.634	0.501	18	0.504	0.776	0.626	16	0.382	0.612	0.489	22
Xian	0.498	0.595	0.546	18	0.454	0.537	0.504	22	0.448	0.509	0.488	20	0.485	0.609	0.543	21	0.467	0.539	0.529	20
Lanzhou	0.324	0.495	0.402	27	0.317	0.499	0.402	26	0.306	0.479	0.387	26	0.404	0.666	0.526	23	0.314	0.485	0.394	26
Xining	0.292	0.336	0.338	30	0.287	0.350	0.340	30	0.283	0.318	0.323	30	0.331	0.422	0.394	30	0.289	0.341	0.342	29
Yinchuan	0.432	0.604	0.518	20	0.422	0.710	0.527	20	0.403	0.631	0.496	19	0.441	0.586	0.519	24	0.414	0.748	0.538	19
Urumqi	0.468	0.815	0.622	14	0.450	0.718	0.564	19	0.444	0.626	0.529	16	0.492	0.727	0.597	20	0.455	0.858	0.629	14

The quartile boxplots of five undesirable output variable specific efficiency scores for all 30 Chinese cities and the cities in the east, central and west China areas are additionally shown in Fig. 4 so as to help us identify the industrial environmental efficiency patters of Chinese major cities during 2006-2010. It can be seen that, both for all 30 Chinese cities as a whole and for cities in three areas, the mediums of the industrial dust emission efficiency scores (DEE) are the lowest (0.52, 0.74, 0.63, 0.49) and the mediums of the industrial waste water discharge efficiency scores (WWDE) are the highest (0.64, 0.85, 0.70, 0.54). Considering the undesirable output variable specific efficiency gaps, the variance of DEE is largest and the variance of the industrial soot emission efficiency scores (SEE) is smallest for east China cities; the variance of the industrial solid waste discharge efficiency scores (SWDE) is largest and the variance of DEE is smallest for central China cities; and the variance of WGEE is largest and the variance of WWDE is smallest for west China cities. Overall, the largest efficiency gap between the best and the worst performed Chinese cities evidences on SWDE, and on the contrary, the smallest efficiency gap exhibits on WWDE. These results indicate that, although cities in different Chinese areas show similar undesirable output variable specific efficiency levels according to the mediums of efficiency scores, the undesirable output variable specific efficiency patterns of cities in three Chinese areas are diversified considering the variances of efficiency scores.

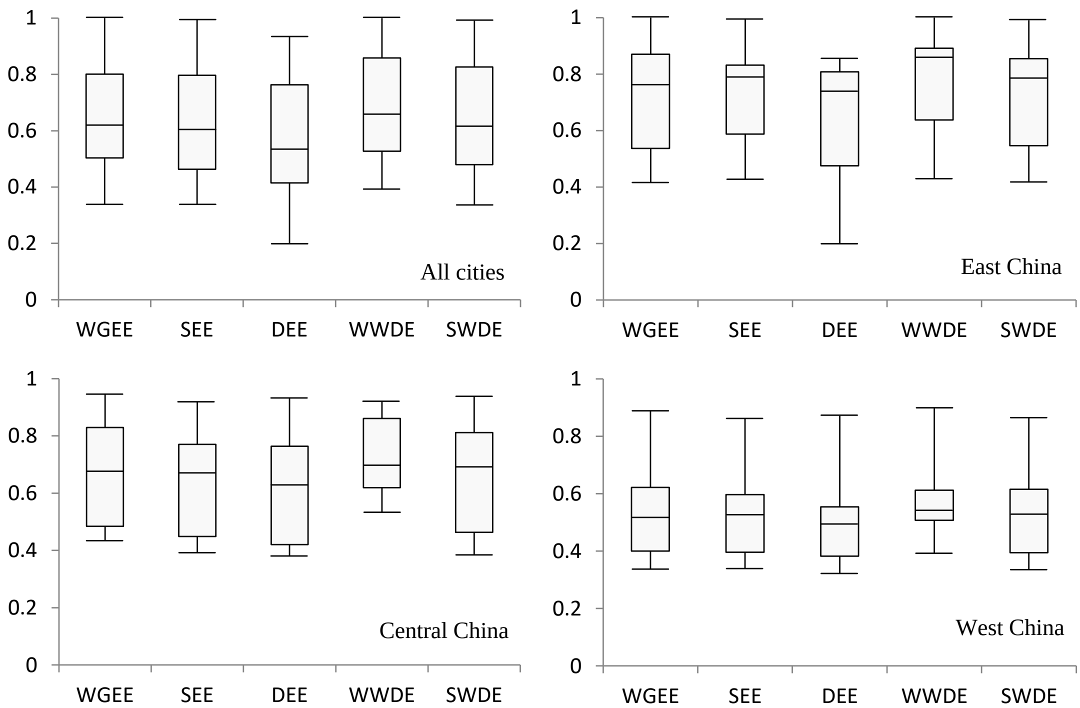

Fig. 4 Industrial undesirable output specific efficiency comparison of Chinese major cities

With regard to the integrated MEA efficiency, the 5 year average efficiency scores of the east, central and west China cities are 0.68, 0.61 and 0.45, respectively, which indicate that if the industrial sectors of all Chinese cities operate on the joint frontier of energy consumption, industrial production, and pollutant emission, there could be on average approximately 32%, 39% and 55% increase spaces on integrated MEA environmental efficiencies for the industrial sectors of the cities in three Chinese areas, respectively. In addition, regarding to the undesirable output variable specific efficiencies, the 5 year average efficiency scores of Chinese 30 major cities are 0.64, 0.63, 0.61, 0.68, and 0.64, thus these 30 cities could on average respectively increase their waste gas emission efficiency, soot emission efficiency, dust emission efficiency, waste water discharge efficiency, and solid waste discharge efficiency in their industrial sectors by approximately 36%, 37%, 39%, 32%, and 36%, if these cities respectively operate on their undesirable output emission or discharge specific frontiers.

Fig. 5 illustrates the radar charts of 5 year average integrated MEA efficiency scores and all variable specific efficiency scores for all 30 Chinese cities in three areas of the east, central and west China. In the left chart, it could be seen that the average IVAE scores are higher than all other efficiency scores for almost all Chinese major cities, which indicates that, on average, the industrial production performances of Chinese cities are better compared with the industrial energy consumption performances and industrial pollutant emission or discharge performances of them. Cities in the east area enjoyed a more balanced environmental efficiency distribution in their industrial sectors, while that of the west China cities are the most unbalanced. The fluctuation on WGEE scores among 30 Chinese cities is higher than that on IVAE and ENEE. The right chart of Fig. 5 specifically shows the distribution of undesirable output variable specific efficiency score among 30 Chinese cities. It can be seen that for all five pollutant emission or discharge efficiencies (WGEE, SEE, DEE, WWDE, SWDE), the unbalances among west China cities are more severe than those among central China cities, and the east China cities have the most balanced pollutant emission or discharge efficiencies. There are also one or two exceptions in all three areas: Shanghai in east China, Taiyuan and Harbin in central China, and Guiyang and Kunming in west China. For example the industrial waste water discharge efficiency of Harbin is relatively higher compared with its other pollutant emission or discharge efficiencies; the waste gas emission efficiency of Guiyang is relatively lower compared with its other pollutant emission or discharge efficiencies. The above results imply that, from the perspective of MEA environmental efficiency patterns, the comparatively low MEA efficiencies are mainly caused by the low energy consumption efficiencies and the low pollutant emission or discharge efficiencies of Chinese major cities. In addition, according to the variable specific efficiency, the most evident or possible efficiency increase potential of each Chinese major city can be identified, and thus the priority for pollutant control or reduction of each city can be particularly arranged by the local government.

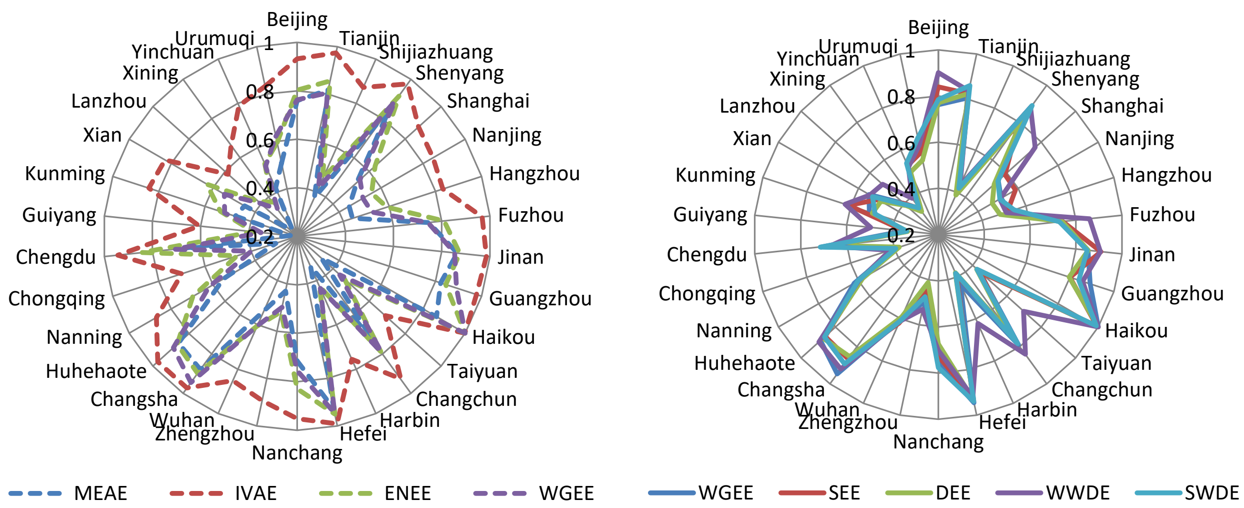

Fig. 5 Average industrial MEA efficiency and specific efficiency of Chinese 30 cities

6 Regional industrial environmental efficiency and economic development of China

Quite a few studies on Environmental Kuznets Curve (EKC) in China have identified the existence of an inverted-U-shaped relationship between the pollutant level and the income level, see (Auffhammer and Carson 2008) and (Song et al. 2008) for ecample, which is, the environmental pressure goes up to a certain level as income goes up, then, when a certain level of income has been reached, the environmental pressure starts to decrease. In general, the EKC indicates how the environmental quality changes as the fortune of a region changes. In this section, we focus on examining whether the EKC relationship exists between the industrial environmental efficiency and the income growth at the city level of China. The environmental pressure is respectively represented by the integrated MEA efficiency and the pollutant emission or discharge efficiencies, in which, high environmental efficiency means less environmental pressure. The income is denoted by regional GDP per capita (*GDPPC*). Referring to (Dinda 2004), we propose the following EKC regression model:

$$E_i = c_i + \beta_1 GDPPC_i + \beta_2 \left(GDPPC_i\right)^2 + \beta_3 \left(GDPPC_i\right)^3 + \boldsymbol{\eta}\mathbf{x}_i + \varepsilon_i \qquad (6)$$

In Model (6), E_i is the industrial environmental efficiency score of *i*th city, c_i is the constant, β_1 to β_3 are the coefficients of the explanatory variables, vector $\mathbf{x}_i$ represents other possible variables that may have influence on the environmental efficiency, vector $\boldsymbol{\eta}$ represents the coefficients of $\mathbf{x}_i$ variables, and ε_i is a random error term.

The regression results are reported in Table 4 and further illustrated in Fig. 6 and Fig. 7. We utilize the Tobit method for the regression, and one additional explanatory variable, the industrial energy consumption per capita (*ENEPC*), is added in the model.

Table 4 Regression results of relationship between income, energy consumption and efficiency

Variables	MEAE	IVAE	ENEE	WGE	SE	DE	WWE	SWE
GDPPC	0.305***	0.185***	0.281***	0.247***	0.254***	0.244***	0.238***	0.262***
	(6.602)[a]	(8.455)	(7.733)	(5.780)	(6.004)	(5.401)	(6.254)	(6.094)
$(GDPPC)^2$	-0.028***	-0.017***	-0.027***	-0.022***	-0.023***	-0.022***	-0.022***	-0.024***
	(-4.914)	(-6.506)	(-6.063)	(-4.324)	(-4.388)	(-4.035)	(-4.732)	(-4.564)
$(GDPPC)^3$	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***
	(4.060)	(5.406)	(5.196)	(3.582)	(3.578)	(3.362)	(3.998)	(3.768)
ENEPC	-0.060***	-0.033***	-0.055***	-0.052***	-0.048***	-0.051***	-0.042***	-0.051***
	(-6.677)	(-7.837)	(-7.700)	(-6.176)	(-5.778)	(-5.724)	(-5.699)	(-6.067)
R^2	0.478	0.547	0.534	0.412	0.442	0.387	0.443	0.427
Adj. R^2	0.460	0.532	0.516	0.391	0.423	0.365	0.424	0.407
AIC[b]	-0.417	-1.913	-0.994	-0.573	-0.595	-0.460	-0.804	-0.559
SC[c]	-0.297	-1.793	-0.868	-0.452	-0.474	-0.340	-0.683	-0.439
Turning point lower (1000￥)	9.21	8.51	8.39	9.11	9.46	9.24	9.15	9.04
Inflection point (1000￥)	11.52	11.46	11.14	11.50	11.69	11.44	11.28	11.53
Turning point upper (1000￥)	13.84	14.41	13.89	13.90	13.91	13.64	13.41	14.02

[a] The value in the parentheses is z-Statistic. Significance levels: * = $p < 0.05$, ** = $p < 0.01$, *** = $p < 0.001$.

[b] AIC is the Akaike info criterion.

[c] SC is the Schwarz criterion.

Overall, the regression results indicate an N-shaped relationship between industrial environmental efficiency and the GDP per capita, which can be seen in Fig. 6 and Fig. 7. As presented in Table 4, a positive coefficient for *GDPPC* associated with a negative coefficient for the quadratic *GDPPC* and a positive coefficient for its cubic term is identified for the integrated MEA environmental efficiency and its every single variable specific efficiency, respectively. This N-shaped relationship implies an environmental efficiency increase (environmental pressure alleviation) at the early stage of income growth, which is followed by an environmental efficiency decrease (environmental pressure aggravation) stage, then, once a certain level of income is reached, a further environmental efficiency increase (environmental pressure alleviation) accrues. As shown in Table 4, all the above coefficients estimated are significant different from zero with the 1% significance levels, and the R^2 values range from 0.39 to 0.55. This result confirms the existence of an N-shaped Environmental Kuznets Curve (in terms of the MEA environmental efficiency – GDP per capita relationship) in the industrial sectors of Chinese major cities. In addition, the coefficient of *ENEPC* is negative and 1% significant indicating that the industrial energy consumption per capita has a negative impact on environmental efficiency, which is, the per capita energy consumption increase will lead to environmental pressure increase or environmental efficiency decrease.

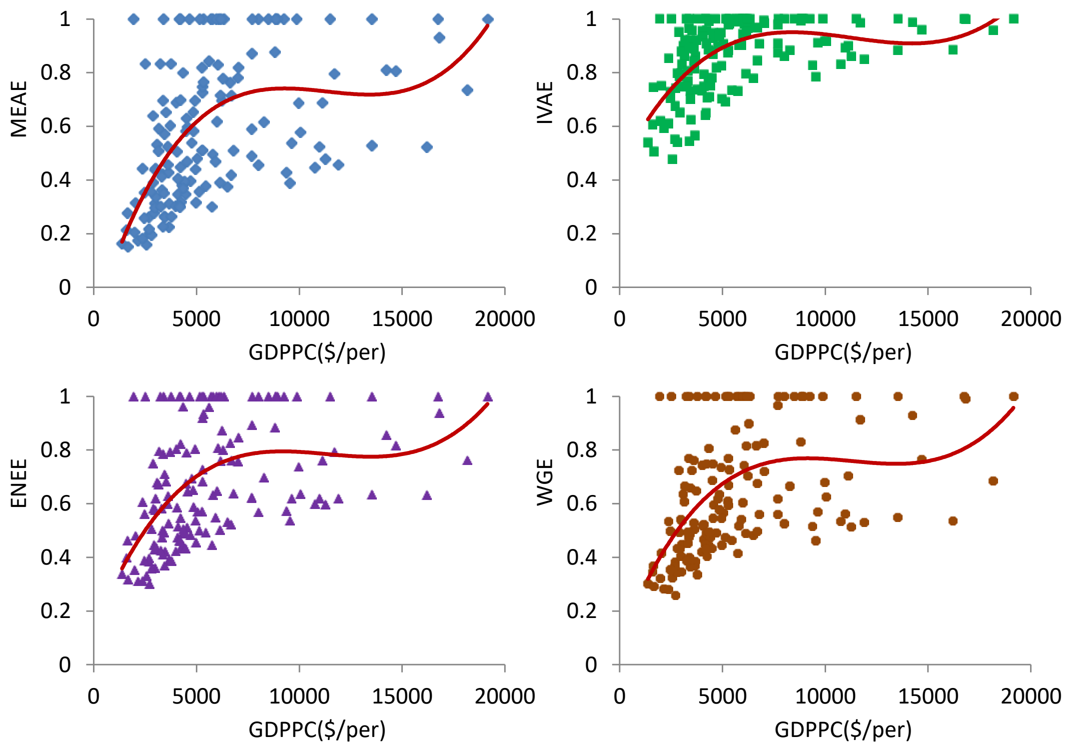

Fig. 6 Relationship between specific efficiencies and GDP per capita

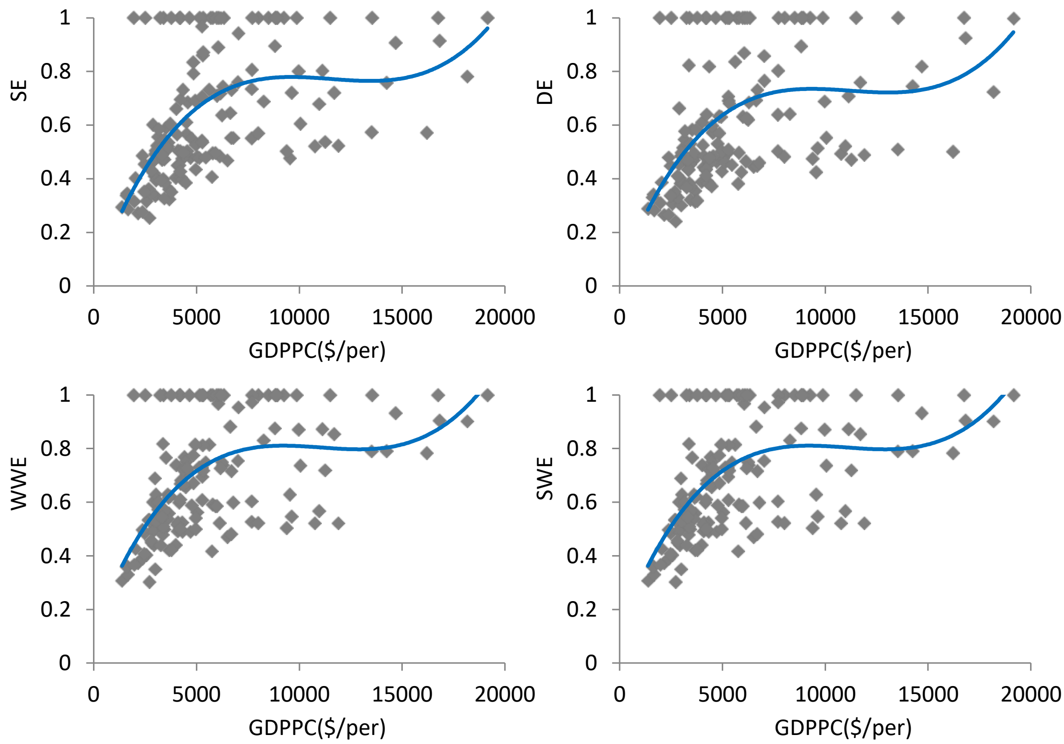

Fig. 7 Relationship between undesirable output specific efficiency and GDP per capita

The turning point and inflection of the N-shaped EKC can be further obtained based on the characteristics of the cubic equation estimated above, which are also reported in Table 4. Two turning points of the integrated MEA efficiency EKC are *GDPPC*=9210 CN￥ (2010 price) and *GDPPC*=13840 CN￥, respectively. Furthermore, the inflection point of the integrated MEA efficiency EKC can be obtained at *GDPPC*=11520 CN￥. This indicates that, in Chinese major cities, the integrated MEA environmental efficiency increases with the rising of income before a certain level of 9210 CN￥ and after a certain level of 13840 CN￥. However, the integrated MEA environmental efficiency decreases with the rising of income between the above two certain levels, in which the efficiency decrease will accelerate before a certain level of 11520 CN￥ and decelerate after that. Similar results on turning points and inflection points can be obtained for the EKCs in terms of IVAE – GDP per capita relationship, ENEE – GDP per capita relationship, and all five pollutant emission or discharge efficiencies – GDP per capita relationships (see Fig. 6 and Fig. 7). Fig. 8 summarized the lower limits, mediums, and upper limits of the lower and upper turning points as well as the inflection points for all the EKCs of variable specific efficiency – GDP per capita relationships. The lower turning points locate in the GDP per capita range of 8391 to 9458 CN￥, the inflection points can be obtained in the range of 11138 to 11686 CN￥, and the upper turning points accrue in the range of 13409 to 14408 CN￥. In general, for Chinese major cities, the industrial environmental performance improves with the income increasing before a certain level of GDP per capita at approximate 9130 CN￥, and after that, the industrial environmental performance declines with the income increasing until a certain level of GDP per capita is reached at approximate 13890 CN￥, then the industrial environmental performance gets back into the tunnel of continuous improving with the rising of income.

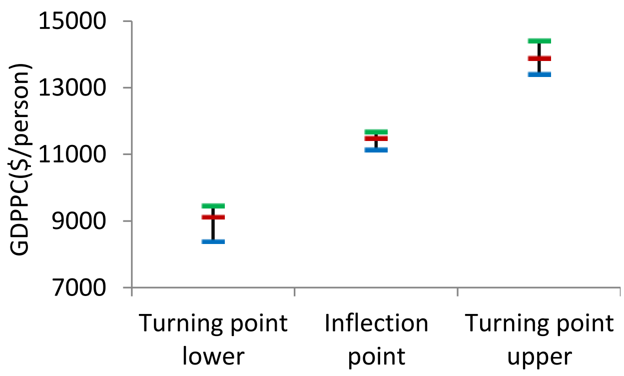

Fig. 8 Ranges of turning point and inflection point of specific efficiency

7 Regional industrial environmental efficiency increase potential of China

According to the MEA efficiency evaluation method, the variable specific inefficiency cities can become efficient on each of their specific efficiency and approach the efficiency frontier through input and undesirable output contraction potential adjustment or output expansion potential adjustment associated with each of the variables. Therefore, we could utilized the MEA method to further measure the potentials on industrial value added increase, industrial energy conservation, and industrial pollutant reduction for each Chinese major city and three Chinese areas.

Based on the definition of variable specific efficiency proposed in definition (4), the energy saving potential of industrial sector in each city can be obtained as $\beta_0^{t*}(x_{i0}^t - d_{i0}^{t*})$, and the ideal energy conservation target after adjustment becomes $x_{i0}^t - \beta_0^{t*}(x_{i0}^t - d_{i0}^{t*})$. Similarly, the industrial value added increase potential and adjustment target are $\beta_0^{t*}(d_{r0}^{t*} - g_{r0}^t)$ and $g_{r0}^t + \beta_0^{t*}(d_{r0}^{t*} - g_{r0}^t)$, and the industrial pollutant (waste gas, soot, dust, waste water, and solid waste) reduction potentials and reduction targets can be presented as $\beta_0^{t*}(b_{f0}^t - d_{f0}^{t*})$ and $b_{f0}^t - \beta_0^{t*}(b_{f0}^t - d_{f0}^{t*})$. Fig. 9 and Fig. 10 respectively present the MEA based variable increase or reduction potentials for Chinese east, central and west areas during 2006-2010.

Fig. 9 shows that the total industrial value added increase potential of all 30 Chinese cities calculates to be 660 billion CN￥ in 2006, which gradually reduced to 287 billion CN￥ in 2010. On average, the total increase potential of cities in the east area takes about 42% of the entire potential of all Chinese major cities, and the percentages of west and central area cities account for about 37% and 21%, respectively. The total industrial energy saving potential of all Chinese major cities in 2006 is 232 million tce which also gradually reduced to 120 million tce in 2010. Cities in the east area have the largest total industrial energy saving potential (40%), followed by the potential of cities in the west (32%) and central (28%) areas. This results indicate that the industrial value added and energy consumption efficiency increase efforts of the cities in the east area is most important, since they will lead to the most significant industrial value added increase and industrial energy conservation effects among all Chinese major cities.

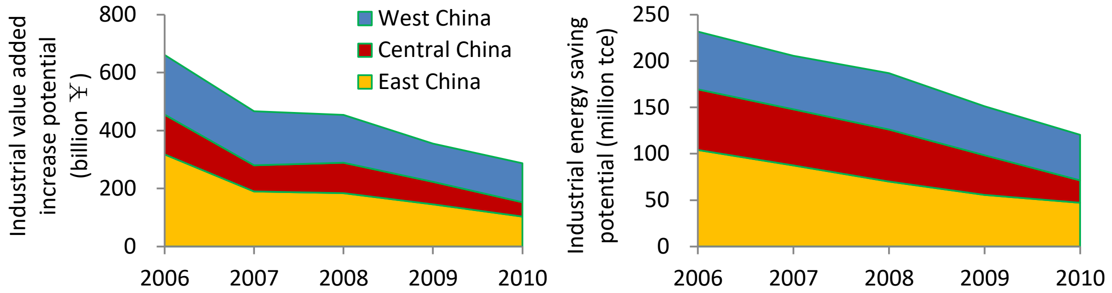

Fig. 9 Industrial value added increase and energy saving potentials of Chinese major cities (2006-2010)

Similarly results can be seen from Fig. 10 that the total volumes of all five industrial pollutant reduction potentials of 30 Chinese cities experienced decrease processes. For example, the industrial waste gas reduction potential of all Chinese major cities decreased from 4115 billion m^3 to 2837 billion m^3 during 2006-2010, and during the same period, the accumulated industrial waste water reduction potential decreased from 2642 million tonnes to 1184 million tonnes. However, the distributions on different pollutant reduction potentials among three Chinese areas vary a lot. East China cities together have the highest percentages on industrial waste gas and waste water reduction potentials (45% and 49%) among all Chinese major cities, and those percentages of central China cities are the lowest (12% and 18%). Different distributions appear in industrial dust and solid waste reduction potentials among three Chinese areas, which is, cities in west China together takes the highest percentages (38% in solid waste reduction potential and 47% in dust reduction potential), and cities in central China together accounts the lowest reduction potential percentages (29% in the former and 26% in the latter). With regard to the industrial soot reduction potential, west China cities have the highest reduction potential percentage of 40%, while east China cities have the lowest percentage of 27%. The above results imply that for different kind of pollutants, the most important emission or discharge reduction area is different; in other words, cities in different Chinese area should have different pollutant reduction priority, which is, east China cities should mainly focus on their industrial waste gas emissions and industrial waste water discharges, while west China cities should pay more attention on their industrial soot and dust emissions, as well as their solid waste discharges.

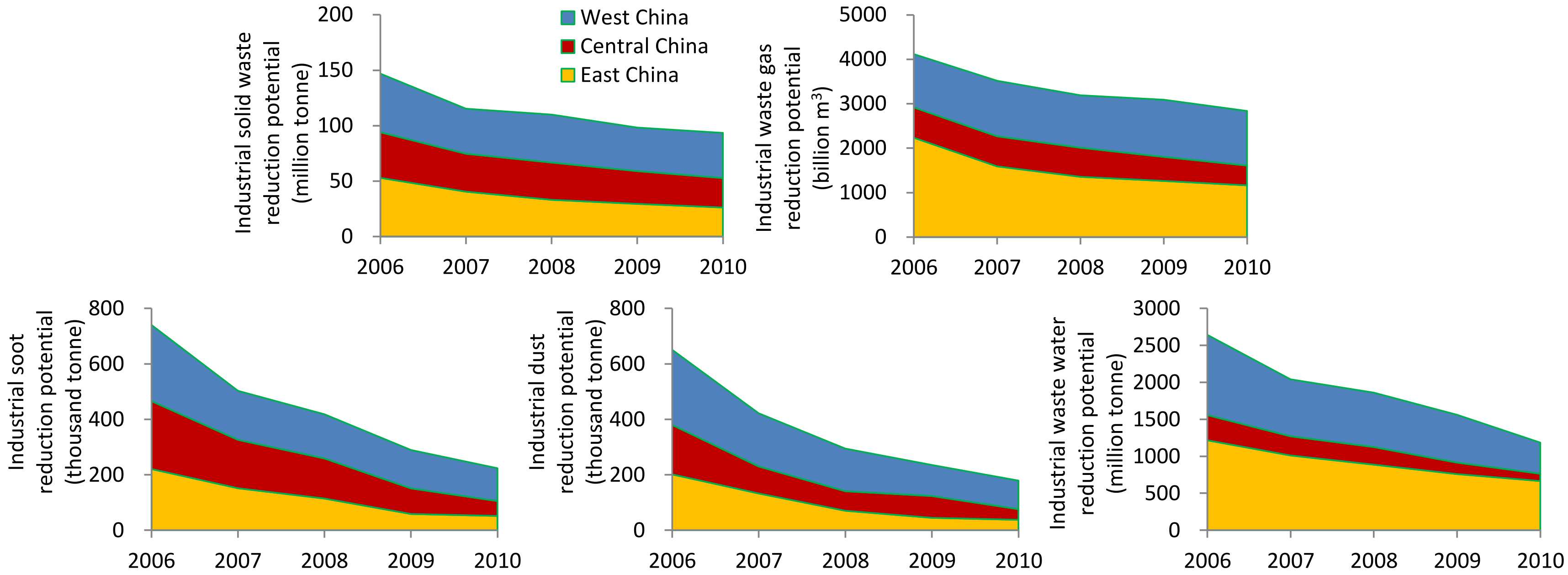

Fig. 10 Industrial undesirable outputs reduction potentials of Chinese major cities (2006-2010)

Fig. 11 additionally illustrates the energy saving potential and the potentials on waste gas, waste water and solid waste reductions, as well as their saving or reduction target of each Chinese major city in 2010. With regard to the industrial energy saving potential, four cities (Shanghai, Chongqing, Shijiazhuang and Nanjing) have the largest saving potential volumes that over 10 million tce, and five other cities (Xining, Guiyang, Taiyuan, Harbin, and Lanzhou) have the highest percentages on saving potentials that above or near 50%. These nine cities are the most critical industrial energy saving areas of China in 2010, in which four cities locate in west China and three cities come from east China. With regard to the industrial waste gas reduction potential, three cities (Chongqing, Shanghai and Nanjing) show the largest absolute potentials over 250 billion m^3, and six cities (Xining, Guiyang, Taiyuan, Shijiazhuang, Chongqing and Lanzhou) show the highest relative potentials above 50%. Half of these eight cities are from west China, and only one city is in central China. All these eight cities are considered the most important industrial waste gas reduction areas of China in 2010. Considering the industrial waste water reduction potential, the cities of Shijiazhuang, Xining, Chongqing, Nanjing, and Hangzhou should play the most important role in China's effort on industrial waste water reduction, since the former two cities hold the highest reduction potential rates (above 50%), and the latter three cities present the largest reduction potential volumes (over 100 million tonnes). Among these five cities, Shijiazhuang, Nanjing and Hangzhou are in east China, and Chongqing and Xining are from west China. Considering the industrial solid waste reduction potential, two cities of Chongqing and Taiyuan evidence the largest volumes on absolute reduction potentials which are over 14 million tonnes, and the absolute reduction potentials of remaining 28 cities are not excess 9 million tonnes. However, according to the relative reduction potentials, another five cities should be paid more attentions on: Xining, Guiyang, Harbin, Shijiazhuang and Lanzhou, whose reduction potential percentages are all above 50%. To sum up, according to the industrial energy saving potential and three major industrial pollutants (waste gas, water and solid) reduction potentials, the efforts from the following cities will have the most significant influence on the effectiveness of industrial energy conservation and pollutant control of entire China, as well as China's industrial environmental performance promotion: Shijiazhuang, Shanghai, Nanjing, Hangzhou, Taiyuan, and Chongqing.

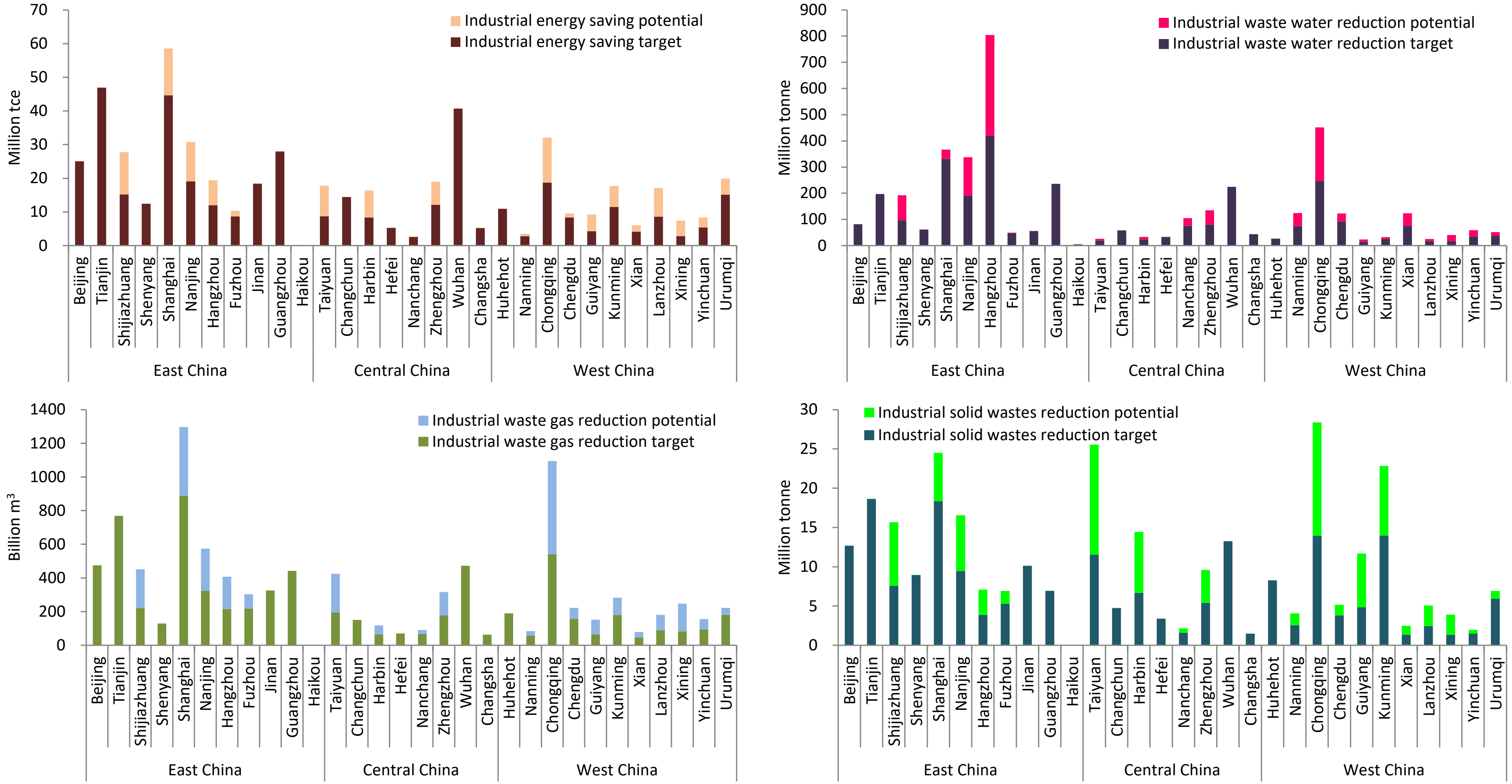

Fig. 11 Industrial energy saving potential and selected undesirable outputs reduction potentials of Chinese 30 cities in 2010

8 Conclusions

We utilize the MEA method in this study to investigate the environmental efficiency levels and patterns of industrial sectors of 30 Chinese major cities, as well as to measure the industrial energy conservation and pollutant reduction potentials and identify the relationship between the environmental pressure and income of Chinese major cities during the period of 2006-2010, so as to get additional insights into the characteristics of regional environmental performance and provided more appropriate and specific policy implications on China's regional environmental management. The main findings of this study include: (i) The economically well developed and technologically advanced east China cities enjoyed higher environmental performances, but cities in west China suffered the lowest environmental efficiency in their industrial sectors. (ii) The MEA efficiency increases of less developed central and west China cities were faster than those of the cities in east China, and thus the inequitable nationwide industrial developments of east, central and west Chinese cities have started to mitigate during the period of 2006-2010. (iii) The west China cities are the main contributors for China's integrated MEA environmental efficiency promotion during 2006-2010 and the relative MEA efficiency decrease cities evenly distributed in China's east, central and west areas. (iv) The difference on MEA efficiency level among three Chinese areas are evenly caused by the differences on IVAE, ENEE and WGEE levels among three Chinese areas, but the difference on MEA efficiency variance among three Chinese areas are mainly caused by the difference on IVAE efficiency variance among three Chinese areas. (v) Although cities in different Chinese areas show similar undesirable output variable specific efficiency levels, the undesirable output variable specific efficiency patterns of cities in three Chinese areas are diversified. (vi) The comparatively low MEA efficiencies are mainly caused by the low energy consumption efficiencies and the low pollutant emission or discharge efficiencies of Chinese major cities, and according to the variable specific efficiency, the most possible efficiency increase potential of each Chinese major city can be identified. (vii) There exists an N-shaped Environmental Kuznets Curve in the industrial sectors of Chinese major cities, and in general, the lower and upper turning points, as well as the inflection point of the N-shaped EKC accrue at *GDPPC*=9130, 13890, and 11480 CN￥, respectively. (viii) The cities in the east area have the largest total industrial energy saving potentials, thus the industrial value added and energy consumption efficiency increase efforts of the cities in this area will lead to the most significant industrial value added increase and industrial energy conservation effects among all Chinese major cities. (ix) Cities in different Chinese area should have different pollutant reduction priority, which is, east China cities should mainly focus on their industrial waste gas emissions and industrial waste water discharges, while west China cities should pay more attention on their industrial soot and dust emissions, and solid waste discharges. (x) According to the industrial energy saving potential and three major industrial pollutants reduction potentials, the efforts from six cities (Shijiazhuang, Shanghai, Nanjing, Hangzhou, Taiyuan, and Chongqing) will have the most significant influence on China's industrial environmental performance promotion.

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