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Regional difference in global unified efficiency of China—Evidence from city-level data

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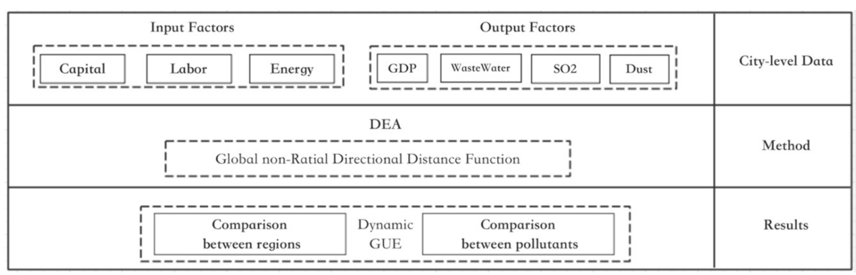
HIGHLIGHTS

- The NDDF method is used to estimate the global unified efficiency (GUE).
- Samples are divided into seven regions based on their geographic locations.
- A global production technology is defined as the union of intertemporal technology.
- The average GUE of each region increases over time.

GRAPHICAL ABSTRACT



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ABSTRACT

As the world's most energy-consuming and carbon-emitting country, China faces enormous pressures on energy conservation and emission reduction, and improving energy efficiency is one of the most important ways to save energy and reduce emissions. Using the city-level panel data in China during 2013–2017, we apply the global non-radial directional distance function (NDDF) to estimate the global unified efficiency (GUE) of each city as well as their driving forces, and identify the change of efficiency performance. The results indicate that the average GUE changed −1.0%, 1.2%, 6.0% and 7.0% during 2013–2014, 2014–2015, 2015–2016 and 2016–2017, respectively. The more developed Central China and the relatively underdeveloped Northwest China have high *GUE*, while the lower *GUE* exists in the Northeast and North China regions with greater industrial transformation and upgrading pressures. In general, the global unified efficiency of each region increases over time.

1. Introduction

Since the beginning of the 21st century, China's energy consumption has grown rapidly and surpassed the United States in 2009, making China the most energy-consuming country in the world (Liu et al., 2018). China's primary energy consumption in 2018 was about 3273.5 million tons of standard oil (Mtoe), accounting for 23.6% of the world's total energy consumption (Fig. 1). With the urbanization and industrialization, China's energy consumption will continue to grow in the future (Lu and Li, 2019; Mi et al., 2018).

Due to the huge energy consumption, China's energy issues and the related environmental issues have once become one of the most concerned research areas. On one hand, energy consumption provides support for the rapid development of China's economy (Shahbaz et al.,

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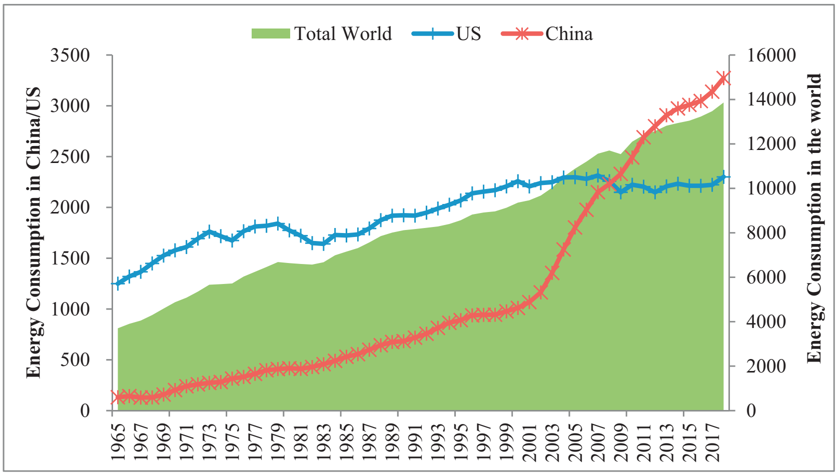

Fig. 1. Primary energy consumption in China, US, and the world (Mtoe).
Source: BP statistical review of the world 2019.

2013), on the other hand, pollutant emissions from huge energy consumption and coal-based energy structure have also caused serious environmental problems (Lin and Zhu, 2018). In particular, the national haze since 2013 has aroused public concern about the environmental issues and resource constraints. It is becoming a consensus that the previous extensive model has been unable to meet the requirements of sustainable development (Zhang et al., 2011).

Energy is one of the most important foundations indispensable for economic and social development, and the misuse of energy will bring a series of environmental problems. Since energy is essential and cannot be overused, improving energy efficiency has become an inevitable choice for energy saving and emission reduction (Zhang and Lin, 2018).

Energy efficiency can be divided into single factor efficiency and total factor efficiency. Single factor energy efficiency, also called energy intensity, is defined as the ratio of energy consumption and total output. As the simple data acquisition and the straightforward results, energy intensity is often used as one of policy target indicators (Cornillie and Fankhauser, 2004; Fisher-Vanden et al., 2004). In December 2016, the National Development and Reform Commission and the National Energy Administration proposed in the “13th Five-Year Plan for Energy Development” that by 2020, the development goal of reducing energy intensity by 15% compared with 2015 will be achieved. Research on single factor energy efficiency is generally based on factor decomposition of energy efficiency indicators through appropriate methods (Karimu et al., 2017; Li and Tao, 2017; Ma et al., 2019).

Total factor energy efficiency is generally defined as the proportion of target energy consumption to actual energy consumption, which can be used to measure the energy-economic efficiency and energy-technology efficiency. Target energy consumption refers to the optimal and feasible energy input, that is, the minimum energy input that can be achieved under specific production conditions. Total factor energy efficiency refers to the utilization efficiency of energy in the production process together with other input factors such as capital, labor, raw materials, etc. Data Envelopment Analysis (DEA) or Stochastic Frontier Approach (SFA) can be used to measure the total factor energy efficiency of different industries or regions (Beltrán-Esteve et al., 2019; Llorca et al., 2017; Sun et al., 2019; Wu et al., 2017).

Although the evaluation of energy intensity is simple and specific, it cannot take into account the substitution between energy and other input factors. The benefit of total factor energy efficiency is to facilitate the evaluation and comparison of efficiency performance across industries or regions (Mardani et al., 2017). Since total factor energy efficiency is derived from the microeconomic theory of total factor productivity, it can not only accurately consider the substitution between input factors, but also reflect the overall utilization efficiency under a certain production technology. As a linear programming method for non-parametric estimation, the biggest advantage of DEA is that it does not need to assume the specific production functional form of the frontier of technology when compared with SFA (Du and Lin, 2017).

Färe et al. (2004) and Färe et al. (2005) emphasized the importance of dividing output variables into desirable outputs and undesired outputs, thus the environmental efficiency can be assessed with DEA method. Zhou and Ang (2008) first divided input variables into energy inputs and non-energy inputs in order to measure the energy efficiency. By applying bootstrap to modify the values based on DEA, Song et al. (2013) analyzed the energy efficiency of BRICS. Sueyoshi and Goto (2011) combine input variable separation with output variable separation to unify all types of efficiency, including operational efficiency, energy efficiency, and environmental efficiency, as “unified efficiency”. Unified efficiency can be defined as the average efficiency of each input-output variable, not only to measure the efficiency of the use of individual input and output variables, but also to measure the comprehensive utilization efficiency between variables. As unified efficiency can be applied under the framework of the total factor energy efficiency, so it is also called total factor unified energy efficiency.

From the perspective of methodology, Mahlberg and Sahoo (2011) proposed a non-radial direction distance function (NDDF) method to simulate the efficiency of energy and carbon dioxide emissions. On this basis, Zhang et al. (2014) proposed a common frontier NDDF approach to measure energy efficiency and technology gaps in the power generation industry, and analyze the impact specific policies on the efficiency of China's fossil fuel power generation. Since NDDF has overcome some of the shortcomings of traditional directional distance functions (DDF), it has been widely used, for example, Wang et al. (2017) estimated the efficiency of China's manufacturing industries with the NDDF method.

In total factor energy efficiency analysis, it is important factors to define the production technology frontier. For the results comparison between various years, Lin and Du (2015) extended the NDDF to global NDDF by the global DEA method which is proposed by Oh (2010), and evaluated the environmental (energy and carbon) efficiency by combining the environmental (energy and carbon) efficiency estimation model in Zhang et al. (2014) and the global DEA method.

Compared with previous studies, we contribute to the existing literature in several ways: On the one hand, previous studies have mostly considered carbon dioxide as an undesirable output, so as to explore the energy-carbon efficiency of various regions (Ramanathan, 2006; Yao et al., 2016; Zhang and Lin, 2018). In contrast, this article considers the emissions of sulfur dioxide, wastewater, and dust as undesired outputs, and explores energy-environmental efficiency. On the other hand, existing studies on China mostly use provincial panel data (Chen and Jia, 2017; Fan et al., 2017). However, as China's provinces may contain dozens of cities, and there is a large gap in the development and efficiency between these cities. Therefore, regional characteristics of energy-environment efficiency may not be accurately described by provincial panel data. In view of this, this paper tries to collect and collates China's city-level panel data, estimate the energy-environmental efficiency of various regions, and analyze the possible influencing factors.

The other parts of this paper are organized as follows. Section 2 is methodology, introducing the method of non-radial directional distance function (NDDF) based on global production technology used in this paper. Section 3 introduces the dataset used in this article and its sources. Section 4 is the result of the empirical analysis and the corresponding discussions. Section 5 concludes and puts forward some related policy implications.

2. Methods

Suppose that there are M cities and each city uses capital (K), labor (L), and Energy (E) as inputs to generate the value added (Y) and pollutants emissions (P). Y and P are the desirable output and undesirable output. The multi-output production technology can be described as follows:

$$Tech = \{(K, L, E, Y, P) : (K, L, E) \text{ can produce } (Y, P)\} \tag{1}$$

where *Tech* is often assumed to satisfy the standard axioms of production theory. For instance, inactivity is always possible, and finite amounts of inputs can only produce finite amounts of outputs. In addition, inputs and desirable output are often assumed to be strongly disposable, thus, the weak-disposability and null-jointness assumption should be imposed on *Tech*, which can be expressed as follows:

a. *If* $(K,L,E,Y,P) \in Tech$ *and* $0 \le \theta \le 1$, *then* $(K,L,E,\theta Y,\theta P) \in Tech$
b. *If* $(K,L,E,Y,P) \in Tech$ *and* $P = 0$, *then* $Y = 0$

Further, the weak-disposability means that pollutant emission reduction is costly, which is accompanied by the decrease in desired output and the null-jointness assumption means that pollutant emissions along with development are inevitable.

Once the environmental production technology *Tech* is specified, the parametric translog/quadratic function or the nonparametric DEA method can be used to specify the production technology. It also matters that whether the environmental production technology should be assumed as variable or constant returns to scale. As pointed out by Picazo-Tadeo et al. (2011) and Picazo-Tadeo et al. (2012), the assumption of constant results to scale in environmental efficiency analysis has the advantages that it can reflect the ration of output to environmental pressure more directly, and it's difficult to consider variable returns to scale in measures of environmental efficiency based on directional distance functions. At the same time, the assumption of constant return to scale is closely related to the weak-disposability property mentioned above.[1] Thus, the environmental production technology *Tech* for M cities exhibiting constant returns to scale can be expressed

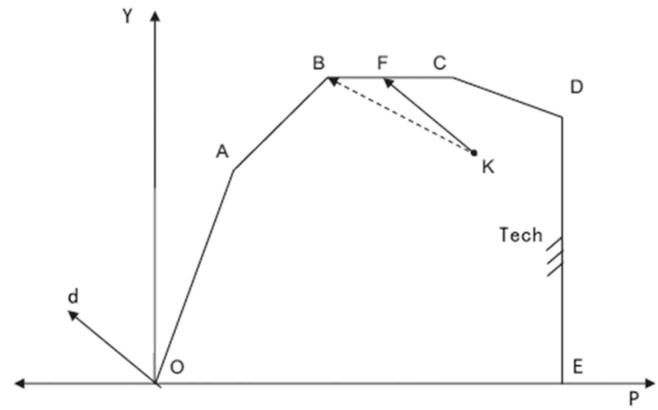

Fig. 2. Illustration of radial and non-radial directional distance functions.

as follows:

$$Tech = \left\{ \begin{array}{c} (K, L, E, Y, P) : \sum_{m=1}^{M} z_m K_m \le K, \sum_{m=1}^{M} z_m L_m \le L, \\ \sum_{m=1}^{M} z_m E_m \le E, \sum_{m=1}^{M} z_m Y_m \ge Y, \sum_{m=1}^{M} z_m P_m = P, z_m \ge 0, m = 1, 2, \cdots, M \end{array} \right\} \tag{2}$$

Chung et al. (1997) firstly used the DDF to examine the environmental efficiency. In general, DDF can achieve such a goal that maximizes desirable outputs while reducing undesirable outputs simultaneously:

$$\overrightarrow{DDF}(K, L, E, Y, P; d) = sup\{\boldsymbol{\beta} : ((K, L, E, Y, P) + d \times \boldsymbol{\beta}) \in Tech\} \tag{3}$$

Picazo-Tadeo and Prior (2009) pointed out that traditional efficiency measurement based on Färe et al. (1989) might fail when the biggest desired output producer is not the biggest polluter. As is shown in Fig. 2, the OABCDE area is the output set defined by Eq. (2). When a decision-making unit at point D moves along the DC direction, there will be an increase in desirable output accompanied by a decrease in undesired output. At the same time, the conventional DDF may overestimate efficiency, and non-radial efficiency measures are often advocated to overcome this limitation because of their advantages (Fukuyama and Weber, 2009; Zhang and Choi, 2013). For point K, if the direction d is taken and the conventional DDF is used, then F is the benchmark point for evaluating K (*KB* and *od* are parallel). But for non-radial DDF, the benchmarking point will be B because it will produce a smaller quantity of undesirable outputs while the same amount of desirable outputs compared with F.

Because non-radial DDF is superior to radial DDF, this paper uses non-radial DDF to measure efficiency in various regions. Following Zhou et al. (2012) and Zhang et al. (2014), the non-radial DDF in this paper is defined as follows:

$$\begin{aligned} &\overrightarrow{NDDF}(K, L, E, Y, P; d) \\ &= sup\{\boldsymbol{w}^T\boldsymbol{\beta} : ((K, L, E, Y, P) + d \times \ diag(\boldsymbol{\beta})) \in Tech\} \end{aligned} \tag{4}$$

where $\boldsymbol{w}^T = (w_K, w_L, w_E, w_Y, w_P)^T$ refers to the weight vector of input and output factors. $\boldsymbol{\beta} = (\beta_K, \beta_L, \beta_E, \beta_Y, \beta_P)$ denotes the inefficiency for each combination of input and output, $d = (-d_K, -d_L, -d_E, d_Y, -d_P)$ is the directional vector, and *diag* refers to diagonal matrices. The same with Zhang et al. (2014), this paper takes both energy and non-energy factors as inputs because we need to estimate the unified efficiency considering energy consumption under a total factor production framework. Thus, a non-radial distance function (NDDF) can be defined when all inefficiencies for inputs and desirable and undesirable outputs are concluded into the objective function and constraints.

[1] Here we just provide a brief review on the assumption of our methodology. There are already several excellent reviews of related discussions in eco-efficiency analysis, see, for example, Picazo-Tadeo et al. (2011) and Picazo-Tadeo et al. (2012).

According to Tulkens and Eeckaut (1995) and Oh (2010), three kinds of production technology sets are defined as follows: contemporaneous production technology, intertemporal production technology, and global production technology. Contemporaneous production technology $Tech_{R_h}{}^C$ indicates the production technology for a specific group R_h in a specific period t, which is defined as: $Tech_{R_h}{}^C = \{(K^t, L^t, E^t, Y^t, P^t) : (K^t, K^t, L^t, E^t, Y^t, P^t)\ :\ (K^t, L^t, E^t)\ can\ produce\ (Y^t, P^t)\}$, $where\ t = 1, \cdots, T$. Intertemporal production technology $Tech_{R_h}{}^I$ of group R_h consists of a single technology constructed from observations over the whole period for group R_h, which is defined as $Tech_{R_h}{}^I = Tech_{R_h}{}^1 \cup Tech_{R_h}{}^{2-} \cup \cdots Tech_{R_h}{}^T$. It is assumed that the observations for one intertemporal production technology are unable to access other intertemporal technologies if there are H different intertemporal technologies. On this basis, global production technology $Tech^G$ is defined as $Tech^G = Tech_{R_1}{}^I \cup Tech_{R_2}{}^I \cup \cdots Tech_{R_H}{}^I$.

It is worth noting that the global production technology envelops all intertemporal production technologies, and it is assumed that all observations can access the global technology through innovation (Zhang and Choi, 2013). By solving the following DEA model, the global NDDF can be computed:

$$
\begin{aligned}
&\overrightarrow{TNDDF}(K, L, E, Y, P; d) = \ max\mathbf{w}^T\boldsymbol{\beta} \\
&s.t. \sum_{t=1}^{T}\sum_{m=1}^{M} z_{m,t}K_{m,t} \le K - \beta_K d_K \\
&\sum_{t=1}^{T}\sum_{m=1}^{M} z_{m,t}L_{m,t} \le L - \beta_L d_L \\
&\sum_{t=1}^{T}\sum_{m=1}^{M} z_{m,t}E_{m,t} \le E - \beta_E d_E \\
&\sum_{t=1}^{T}\sum_{m=1}^{M} z_{m,t}Y_{m,t} \ge Y + \beta_Y d_Y \\
&\sum_{t=1}^{T}\sum_{m=1}^{M} z_{m,t}P_{m,t} = P - \beta_P d_P \\
&z_{m,t} \ge 0, m = 1, 2, \ldots, M, \\
&t = 1, 2, \ldots, T, \beta_K, \beta_L, \beta_E, \beta_Y, \beta_P \ge 0
\end{aligned}
\tag{5}
$$

Table 1
Descriptive statistics for variables.

Region	Variable	Unit	Obs	Mean	Std. dev.	Min	Max
Northeast China	Labor	Ten thousand	165	131.9	245.8	15.8	1730.0
	Capital	Billion yuan	165	872.7	1008.0	132.4	5816.0
	Electricity	10 million kWh	165	136.0	215.6	7.8	1070.0
	GRP	Billion yuan	165	310.0	465.0	41.0	2800.0
	Dust	Thousand ton	165	92.0	257.4	4.6	3200.0
	So2	Thousand ton	165	74.7	52.3	2.0	282.8
	Waste water	Million ton	165	53.4	48.3	3.7	277.5
North China	Labor	Ten thousand	160	77.8	78.8	8.8	369.2
	Capital	Billion yuan	160	872.7	1008.0	132.4	5816.0
	Electricity	10 million kWh	160	72.9	71.1	6.7	288.0
	GRP	Billion yuan	160	163.0	189.0	21.3	773.0
	Dust	Thousand ton	160	35.7	32.5	0.7	166.6
	So2	Thousand ton	160	34.3	43.8	0.5	446.2
	Waste water	Million ton	160	39.9	55.6	2.7	401.5
East China	Labor	Ten thousand	390	176.0	186.5	10.7	1350.0
	Capital	Billion yuan	390	872.7	1008.0	132.4	5816.0
	Electricity	10 million kWh	390	131.2	191.8	7.0	1590.0
	GRP	Billion yuan	390	351.0	371.0	46.2	3010.0
	Dust	Thousand ton	390	34.8	29.2	1.0	154.0
	So2	Thousand ton	390	39.6	33.4	1.3	206.7
	Waste water	Million ton	390	98.3	94.8	4.9	669.2
Central China	Labor	Ten thousand	210	114.7	78.8	17.5	448.3
	Capital	Billion yuan	210	872.7	1008.0	132.4	5816.0
	Electricity	10 million kWh	210	73.8	83.8	9.0	469.6
	GRP	Billion yuan	210	231.0	209.0	36.6	1340.0
	Dust	Thousand ton	210	23.5	23.3	0.6	144.2
	So2	Thousand ton	210	33.6	29.1	0.3	130.5
	Waste water	Million ton	210	54.8	39.5	0.6	193.9
South China	Labor	Ten thousand	175	131.4	185.2	10.2	941.1
	Capital	Billion yuan	175	872.7	1008.0	132.4	5816.0
	Electricity	10 million kWh	175	141.7	218.0	2.3	971.6
	GRP	Billion yuan	175	275.0	416.0	42.4	2250.0
	Dust	Thousand ton	175	16.8	17.8	0.0	92.3
	So2	Thousand ton	175	22.9	21.1	0.5	112.1
	Waste water	Million ton	175	59.2	53.5	5.1	284.0
Southwest China	Labor	Ten thousand	155	131.3	263.4	15.1	1550.0
	Capital	Billion yuan	155	872.7	1008.0	132.4	5816.0
	Electricity	10 million kWh	155	72.1	143.2	4.0	908.0
	GRP	Billion yuan	155	204.0	324.0	24.9	1950.0
	Dust	Thousand ton	155	21.5	29.3	1.4	214.8
	So2	Thousand ton	155	48.0	72.5	0.8	494.4
	Waste water	Million ton	155	41.0	56.4	0.8	355.2
Northwest China	Labor	Ten thousand	90	75.1	73.5	12.9	370.3
	Capital	Billion yuan	90	872.7	1008.0	132.4	5816.0
	Electricity	10 million kWh	90	56.4	82.4	1.4	446.1
	GRP	Billion yuan	90	147.0	137.0	25.2	747.0
	Dust	Thousand ton	90	26.4	41.5	1.2	254.0
	So2	Thousand ton	90	37.0	42.0	2.5	200.8
	Waste water	Million ton	90	26.9	23.3	1.4	136.9

Table 2
Descriptive statistics for variables.

Item	Labor		Capital		Electricity		GRP	
Unit	10 thousand		Billion Yuan		10 million kWh		Billion yuan	
	Average	Growth rate	Average	Growth rate	Average	Growth rate	Average	Growth rate
Northeast China	131.94	1.14	872.65	9.64	135.99	1.39	310.18	3.96
North China	77.84	−2.02	541.34	6.73	72.90	1.77	163.00	−0.99
East China	176.01	6.05	894.64	9.28	131.25	5.38	350.82	6.99
Central China	114.70	3.71	602.05	12.83	73.76	2.80	231.19	7.21
South China	131.38	3.92	502.14	8.84	141.68	6.52	274.87	7.15
Southwest China	131.29	0.70	567.46	11.54	72.11	5.42	203.70	7.93
Northwest China	75.12	3.49	455.73	17.53	56.37	12.46	147.29	13.55

Item	SO2		Dust		Waste Water	
Unit	Thousand ton		Thousand ton		Million ton	
	Average	Growth rate	Average	Growth rate	Average	Growth rate
Northeast China	74.72	−22.73	92.00	−21.85	53.43	−11.42
North China	34.25	−21.49	35.68	−8.20	39.90	−12.17
East China	39.65	−14.57	34.82	1.37	98.28	−7.01
Central China	33.60	−27.30	23.54	−5.80	54.81	−14.65
South China	22.91	−23.01	16.77	−0.03	59.24	−11.13
Southwest China	48.00	−16.63	21.50	−4.85	40.99	−9.31
Northwest China	36.95	−12.37	26.41	−10.92	26.94	−2.20

Following Zhou et al. (2012) and Zhang et al. (2014), the weight vector is set as (1/9, 1/9, 1/9, 1/3, 1/3) and the directional vector is set as $(-K, -L, -E, Y, -P)$. Thus, the weights for three inputs, single desirable output and single undesirable output are equal to each other, and the resulting model can be used to estimate the degrees to which the output is increased and the input factors and pollutant emissions are reduced non-proportionally. The global unified efficiency (*GUE*) index for each city is defined as follows:

$$\begin{aligned} GUE_g &= \frac{1}{4}\left[\frac{(K-\beta_K^*K)/(Y+\beta_Y^*Y)}{K/Y}+\frac{(L-\beta_K^*L)/(Y+\beta_Y^*Y)}{L/Y}+\frac{(E-\beta_K^*E)/(Y+\beta_Y^*Y)}{E/Y}+\frac{(P-\beta_K^*P)/(Y+\beta_Y^*Y)}{P/Y}\right] \\ &= \frac{1}{4}\left[\frac{(K-\beta_K^*K)/K}{(Y+\beta_Y^*Y)/Y}+\frac{(L-\beta_K^*L)/L}{(Y+\beta_Y^*Y)/Y}+\frac{(E-\beta_K^*E)/E}{(Y+\beta_Y^*Y)/Y}+\frac{(P-\beta_K^*P)/P}{(Y+\beta_Y^*Y)/Y}\right] \\ &= \frac{1}{4}\left(\frac{1-\beta_K^*}{1+\beta_Y^*}+\frac{1-\beta_L^*}{1+\beta_Y^*}+\frac{1-\beta_E^*}{1+\beta_Y^*}+\frac{1-\beta_P^*}{1+\beta_Y^*}\right) \\ &= \frac{1/4[(1-\beta_K^*)+(1-\beta_L^*)+(1-\beta_E^*)+(1-\beta_P^*)]}{1+\beta_Y^*}=\frac{1-1/4(\beta_K^*+\beta_L^*+\beta_E^*+\beta_P^*)}{1+\beta_Y^*} \end{aligned} \tag{6}$$

where $\beta_K^*, \beta_L^*, \beta_E^*, \beta_P^*$, and β_Y^* are the optimal solutions of Eq. (5) based on the global production technology $Tech^G$.

The values of *GUE* is between 0 and 1, and the higher the value, the higher the efficiency. That is to say, if the *GUE* value of one city is equal to 1, then this city performs the best unified efficiency which located exactly on the technology frontier. It should be pointed out that the *GUE* in this paper is defined on the global production technology, which is constructed from all observations over the whole period for all cities.

In order to measure changes of the *GUE* on global production technology for period between t and $t+1$, the metafrontier Malmquist–Luenberger index of GUE *MGUE* is defined as follows:

$$MGUE = \frac{GUE_g^{t+1}}{GUE_g^t} \tag{7}$$

MGUE can reflect the unified efficiency change. According to Zhang and Choi (2013), *MGUE* can be decomposed into various components, including efficiency change, technical change and technical leadership change.[2]

[2] See Zhang and Choi (2013) for details of decomposition process.

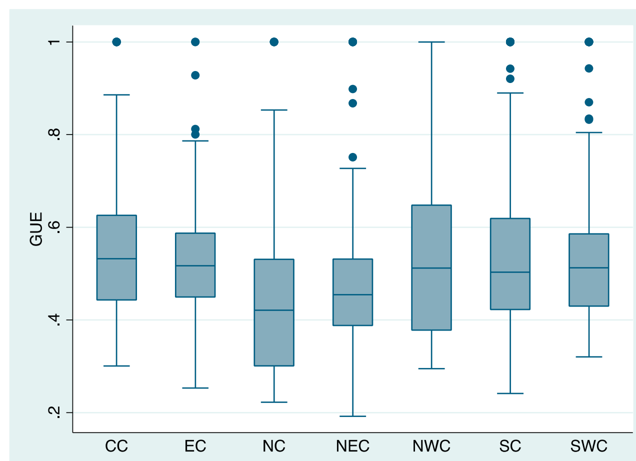

Fig. 3. Box diagram of average *GUE* in each region NEC, NC, EC, CC, SC, SWC and NWC indicates Northeast China, North China, East China, Central China, South China, Southwest China and Northwest China, respectively.

3. Data

The input factors used in this paper include labor, capital and electricity consumption. Desirable output for each city is GRP[3] and undesired outputs include sulfur dioxide, wastewater, and dust. All the input and output variables are city-level.

(Beltrán-Esteve et al., 2019) Labor. The number of employee is used to indicate labor input in each city, which contains persons employed in the urban units at year-end, and persons employed in private enterprises and self-employed individuals in urban areas. These data are from the *China City Statistical Yearbook*.

(Chen and Jia, 2017) Capital. Perpetual Inventory Method proposed by Goldsmith (1951) is used in this paper to estimate the capital stock

[3] Gross Regional product (GRP) is a monetary measure of the market value of all final goods and services produced in a region or subdivision of a country in a period of time. For further details see: https://unstats.un.org/unsd/economic_stat/China/background_paper_on_GRP.pdf

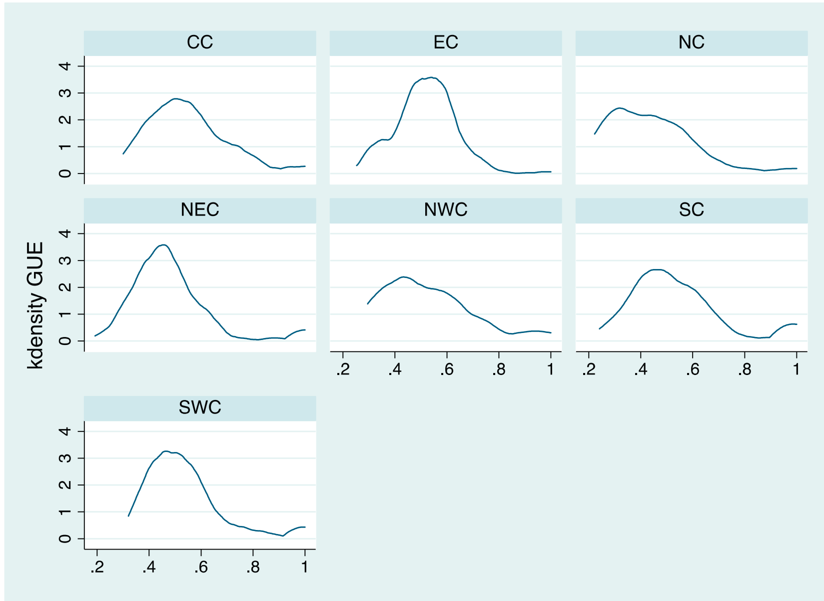

Fig. 4. Kdensity of average GUE in each region. NEC, NC, EC, CC, SC, SWC and NWC indicates Northeast China, North China, East China, Central China, South China, Southwest China and Northwest China, respectively.

of each city, which can be expressed as follows:

$$K_t = I_t + (1-\delta_t) \times K_{t-1} \quad (8)$$

where K_t represents the capital stock in year t, I_t represents the newly added investment in year t, and δ_t represents the depreciation rate. The newly added investment and the depreciate rate can be obtained as follows:

$$I_t = FO_t - FO_{t-1} \quad (9)$$

$$\delta_t = \frac{(FO_t - FN_t) - (FO_{t-1} - FN_{t-1})}{FO_{t-1}} \quad (10)$$

where FO_t and FN_t represent the original value and the net value of fixed assets in year t, respectively. FO_t and FN_t are from the city-level and province-level *China Statistical yearbook*, the capital stock in the prime year is the net value of fixed asset in 2005. All the asset values are converted into constant price in 2005 according to the price index of fixed asset investment.

(Cornillie and Fankhauser, 2004) Electricity consumption. Data of energy consumption at city level are unavailable. Since energy consumption and electricity consumption are highly correlated in most regions, energy input of each city is represents by the electricity consumption following by Lin and Zhu (2018),[4] which is available from the *China City Statistical Yearbook*.

(Du and Lin, 2017) Desired ouputs. Desired output of each city in this paper is represented by its GRP. GRP of each city in nominal prices can be obtained from the *China City Statistical Yearbook*. With the help of producer price index provided by the *National Statistical Bureau*, we can get the GRP at constant price.

(Fan et al., 2017) Undesired outputs. Undesirable outputs include sulfur dioxide emission, waste water emission and dust emission of each city, which can be obtained from the *China City Statistical Yearbook*.

The sample interval studied in this paper is 2013–2017. For the convenience of comparison, cities are divided into seven regions based on their geographical locations according to Liu and Lin (2019): Northeast China (NEC), North China (NC), East China (EC), Central China (CC), South China (SC), Southwest China (SWC) and Northwest China (NWC). Northeast China includes Liaoning, Jilin and Heilongjiang; North China includes Hebei, Shanxi, Inner Mongolia, Beijing and Tianjin; East China includes Shandong, Jiangsu, Anhui, Zhejiang, Fujian, Jiangxi and Shanghai; Central China includes Henan, Hubei and Hunan; South China includes Guangdong, Guangxi and Hainan; Southwest China includes Yunnan, Guizhou, Sichuan and Tibet; Northwest China includes Xinjiang, Shaanxi, Ningxia, Qinghai and Gansu. The statistic description can be seen in Table 1.

Due to the large differences in economic aggregates and industrial structures between various regions, input factors and the growth rates in different regions are significantly different (Table 2). That is, production technologies markedly different in different regions. Ignoring regional technology differences will lead to erroneous results (Yao et al., 2016). From this perspective, it is necessary to divide 269 sample cities into different regions for analysis. Despite this, it is assumed that the global production technology envelops all intertemporal and intergroup production technologies, and all DMUs can access the global technology through innovation.

4. Results and discussions

The estimation results of GUE indicate that there is a big difference in the global unified efficiency between various regions in China (Fig. 3). In all seven regions, the highest average GUE appeared in Central China, Northwest China and East China. The average GUE in South China and Southwest China are at a medium level, while North China and Northeast China have the lowest average GUE.

The above unified efficiency is consistent with our intuitive experience. The northeast region is China's traditional heavy industry base. High energy consumption pollution are a typical characteristics of energy and resource-intensive heavy industries (Lin and Liu, 2017). The industrial structure dominated by heavy industry in the Northeast has caused high energy consumption and high emissions in this region. It can also be seen from Table 2 that the energy consumption in the North China is similar to that in the Central China and South China, but its SO2 and dust emissions are much higher than the other two regions. North China is also one of the lowest areas of GUE. That is partly because North China is one of the largest coal-producing and coal-consuming area in China. Due to its serious environmental issues, it is

[4] The electricity consumption of each city in 2018 has been converted into electricity consumption in the municipal district, in order to be consistent with data of 2013–2017.

Table 3
Statistical description of *MGUE*.

Region	Obs	Mean	Std. dev.	Min	Max
Northeast China	132	1.018	0.156	0.486	1.531
North China	128	0.983	0.154	0.553	1.492
East China	312	1.027	0.130	0.626	1.843
Central China	168	1.051	0.113	0.77	1.455
South China	140	1.062	0.193	0.666	2.45
Southwest China	124	1.063	0.218	0.611	2.418
Northwest China	72	1.020	0.225	0.51	2.159
National average	1076	1.033	0.164	0.486	2.450

Table 4
MGUE of each region during 2013–2017.

Region	2013–2014	2014–2015	2015–2016	2016–2017
Northeast China	0.964	1.025	1.084	0.999
North China	0.864	0.994	0.994	1.078
East China	1.009	0.989	1.060	1.050
Central China	1.002	1.022	1.112	1.069
South China	1.070	1.019	1.069	1.092
Southwest China	1.032	1.055	1.044	1.092
Northwest China	0.924	1.004	1.016	1.136
National average	0.990	1.012	1.060	1.070

also a key area for pollution prevention and control. Tangshan, a city with the most concentrated iron and steel industry in China which locates in Hebei Province, is a typical representative. According to the *National Bureau of Statistics*, the steel production capacity of Tangshan accounts for 55% of Hebei Province and 13% of the whole country. At the same time, Tangshan is also one of the most polluted cities in China, so the *GUE* of Tangshan is relatively low.

From the perspective of *GUE*, Central China and Northwest China are the regions with the best unified efficiency performance in China, but the impact mechanisms of *GUE* in these two regions may be different. For Central China, as one of the most developed regions in China, Central China region has high unified efficiency. Since the industrial structure is dominated by the tertiary industry, the energy intensity and pollutant emission levels in Central China are lower than those in other regions dominated by the secondary industry. For Northwest China, although the Northwest China has the largest area, input factors including labor, capital and energy, together with pollutant emissions in this region are relatively low. In general, the more developed Central China and the relatively underdeveloped Northwest China have high *GUE*, while the lower *GUE* exists in the Northeast and North China regions with greater industrial transformation and upgrading pressures. Northeast and North China are regions where China's heavy industry and resources are relatively concentrated. To some extent, this reflects a "resource curse" on efficiency. The average *GUE* in each region can also be reflected by the kernel density (kdensity) in Fig. 4.

In order to examine the change of unified efficiency, we also calculate the *MGUE* of each city. As is shown in Table 3, the *MGUE* of National average and all regions except North China are >1, indicating that the unified efficiency is constantly improving during 2013–2017. The average *MGUE* of North China during this period is <1, indicating that the unified efficiency has decreased.

In order to better explain the change in *GUE*, the *DGUE* of each region has been shown in Table 4. *GUE*s in East China, Central China, South China and Southwest China were increasing (*DGUE* > *1*), and the *GUE*s in Northwest China were increasing during 2015–2017. The performances of North China and Northeast China in *DGUE* were relatively poor, which indicates that the unified efficiency of these two regions were relatively low, and the improvement over these years was not obvious. The national average of *DGUE* was <1 during 2013–2014, and larger than 1 in the rest of these years, indicating that the national GUE was improving over time. Similar conclusions can also be obtained from the box diagrams in Fig. 5.

The estimation of *GUE* depends on the type and emissions of undesired outputs in the model. In the previous *GUE* estimation process, SO2, wastewater and dust are jointly selected as undesired outputs. Therefore, it is possible to measure the overall efficiency of each city when considering the above three pollutant emissions. Next, we measure the efficiency for specific pollutants of each city by separately treating each pollutant as an undesired output. *GUE_dust*, *GUE_SO2* and *GUE_WW* represent the global unified efficiency when dust, SO2 and waste water emission are selected as undesired outputs, respectively. As is shown in Table 5 and Fig. 6, estimations results are similar. The efficiency in North China and Northeast China were relatively low, while those in Central China, South China and Northwest China were relatively high.

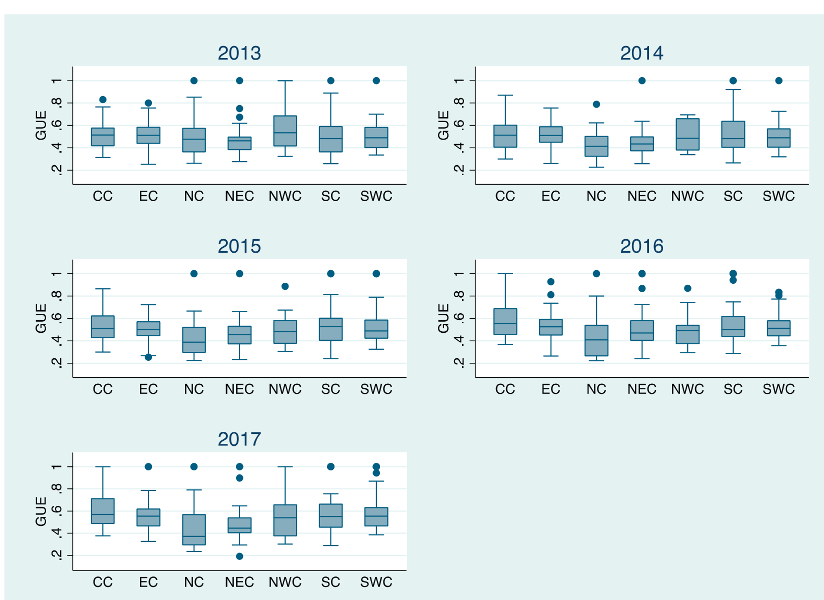

Fig. 5. Box diagrams of average *GUE* in each region during 2013–2017. NEC, NC, EC, CC, SC, SWC and NWC indicates Northeast China, North China, East China, Central China, South China, Southwest China and Northwest China, respectively.

Table 5
Average *GUE* considering different undesired outputs.

Region	Items	Obs	Mean	Std. dev.	Min	Max
Central China	GUE_dust	210	0.538	0.151	0.272	1.000
	GUE_SO2	210	0.512	0.137	0.291	1.000
	GUE_WW	210	0.473	0.119	0.310	1.000
East China	GUE_dust	390	0.510	0.122	0.227	1.000
	GUE_SO2	390	0.498	0.117	0.233	1.000
	GUE_WW	390	0.424	0.086	0.280	0.728
North China	GUE_dust	160	0.414	0.165	0.179	1.000
	GUE_SO2	160	0.419	0.157	0.193	1.000
	GUE_WW	160	0.432	0.163	0.239	1.000
Northeast China	GUE_dust	165	0.464	0.158	0.160	1.000
	GUE_SO2	165	0.467	0.155	0.169	1.000
	GUE_WW	165	0.428	0.127	0.240	1.000
Northwest China	GUE_dust	90	0.505	0.165	0.232	1.000
	GUE_SO2	90	0.476	0.149	0.252	1.000
	GUE_WW	90	0.490	0.130	0.299	1.000
South China	GUE_dust	175	0.530	0.179	0.254	1.000
	GUE_SO2	175	0.512	0.166	0.238	1.000
	GUE_WW	175	0.482	0.161	0.234	1.000
Southwest China	GUE_dust	155	0.512	0.146	0.268	1.000
	GUE_SO2	155	0.482	0.125	0.260	1.000
	GUE_WW	155	0.485	0.135	0.304	1.000

Table 6
Average *MGUE* considering different undesired outputs.

Region	Items	Obs	Mean	Std. dev.	Min	Max
Central China	*MGUE*_Dust	168	1.023	0.123	0.630	1.582
	*MGUE*_SO2	168	1.065	0.144	0.672	1.622
	*MGUE*_WW	168	1.029	0.151	0.793	1.73
East China	*MGUE*_Dust	312	1.024	0.124	0.608	1.803
	*MGUE*_SO2	312	1.034	0.148	0.499	1.982
	*MGUE*_WW	312	1.009	0.113	0.688	1.629
North China	*MGUE*_Dust	128	0.989	0.138	0.600	1.403
	*MGUE*_SO2	128	0.978	0.160	0.509	1.517
	*MGUE*_WW	128	1.015	0.198	0.636	1.817
Northeast China	*MGUE*_Dust	132	0.993	0.146	0.576	1.420
	*MGUE*_SO2	132	1.014	0.153	0.570	1.508
	*MGUE*_WW	132	1.007	0.169	0.573	1.765
Northwest China	*MGUE*_Dust	72	1.002	0.150	0.534	1.442
	*MGUE*_SO2	72	0.998	0.158	0.509	1.563
	*MGUE*_WW	72	1.020	0.179	0.621	1.880
South China	*MGUE*_Dust	140	1.037	0.151	0.637	1.860
	*MGUE*_SO2	140	1.060	0.150	0.622	1.973
	*MGUE*_WW	140	1.039	0.140	0.731	1.930
Southwest China	*MGUE*_Dust	124	1.040	0.198	0.627	2.682
	*MGUE*_SO2	124	1.058	0.225	0.525	3.046
	*MGUE*_WW	124	1.044	0.177	0.680	1.723

In view of the GUE average of 2013–2017, *GUE_dust* in Central China was the highest, *GUE_SO2* was the highest in Central China and South China, and *GUE_WW* was the highest in Northwest China. *GUE_dust* and *GUE_SO2* is the lowest in North China, and *GUE_WW* is the lowest in Northeast China.

Estimation results of average *MGUE* considering different undesired outputs are shown in Table 6. *MGUE* indicates the improvement or degradation of the unified efficiency in the corresponding area. *MGUEs* considering all three pollutant emissions in Central China, East China, South China and Southwest China were >1, indicating that the unified efficiency in these regions were improving during 2013–2017. *MGUE* of dust and SO2 in North China, *MGUE* of dust in Northeast China, and *MGUE* of SO2 in Northwest China were <1, indicating that the corresponding efficiency performance in these regions had been deteriorated. In general, *MGUE* considering individual and integrated pollutant emissions were roughly the same.

5. Conclusions and policy implications

Using the non-radial directional distance function (NDDF) method, we estimated China's global unified efficiency index (*GUE*) with a city-level dataset. The estimation results of *GUE* indicate that the energy-environmental efficiency of Central, Northwest and East China are relatively high, while that of North and Northeast China are relatively low. The results of metafrontier Malmquist–Luenberger index *MGUE* show that the efficiency in most regions increases over time. Simultaneously, in areas with higher *GUE*, *MGUE* is also relatively high and >1, while in areas with lower *GUE*, *MGUE* is lower and more likely to be <1.

North China and Northeast China are the regions with high industrial transformation and upgrading pressure, which are also facing greater pressure on energy efficiency improvement and environmental protection. Although lots of plans have been introduced by the governments, such as Air Pollution Control Plan, and the Transformation and Upgrading of Resource-based Cities, the effect is still not obvious. In

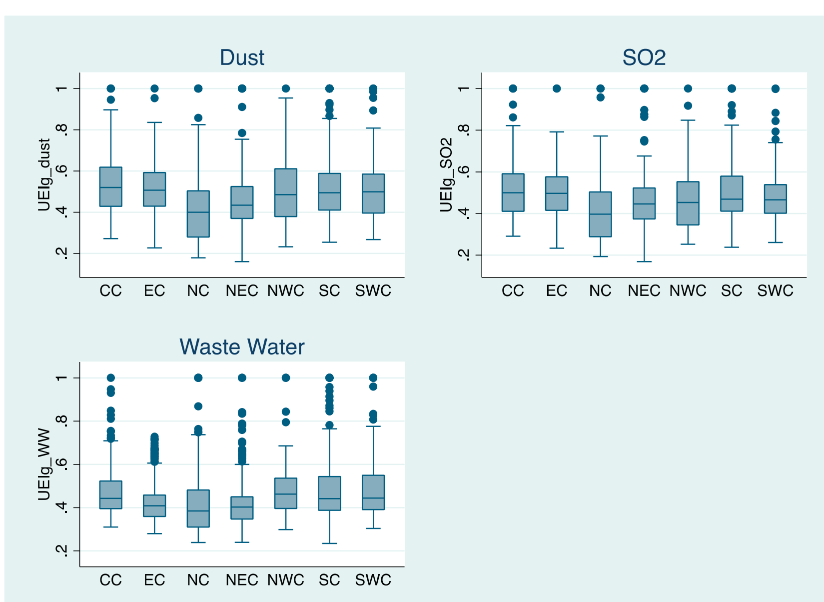

Fig. 6. Box diagrams of average *GUE* considering r different undesired outputs. |NEC, NC, EC, CC, SC, SWC and NWC indicates Northeast China, North China, East China, Central China, South China, Southwest China and Northwest China, respectively.

fact, the experience of Central China has shown that the transformation of industrial structure and the improvement of unified efficiency is complementary. As previously analyzed, the reason why *GUE* is relatively high in Central China is due to its relatively developed economy and its industrial structure dominated by the tertiary industry.

Although the results of *GUE* under various pollutants are similar, there are still some differences. For example, *GUE* corresponding to waste water (*GUE_WW*) in North China is relatively better, when compared with the *GUE* corresponding to SO2 and dust (*GUE_SO2* and *GUE_Dust*) in this area. The same is true for *MGUE* of North China (*GUE_WW* > *1*, while *GUE_SO2* and *GUE_Dus* < *1*). This is related to the energy consumption structure of North China, which is dominated by coal. Coal is the main source of sulfur dioxide and dust emissions, but the impact on waste water is relatively small. This requires us to take targeted measures in accordance with the characteristics of each region in the process of environmental governance.

Declaration of competing interest

This manuscript has not been published and is not under consideration for publication elsewhere. We have no conflicts of interest to disclose.

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