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Sustainable water use and water shadow price in China's urban industry

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ABSTRACT

China is faced with a serious water shortage problem, and industrial sector is a major water consumer. How to improve the efficiency of industrial water use is extremely important for sustainable use of water in China. This paper applies a global non-radial directional distance function (GNDDF) to measure the green use efficiency of industrial water (GUEIW) incorporating undesirable outputs during 2004–2012. We calculate the two components of GUEIW named economic efficiency of industrial water (ECEIW) and economic efficiency of industrial water (ENEIW), and the shadow price of industrial water to explore the bias between the actual prices and the shadow ones. The results show that the GUEIW shows a W type curve over the study period, and its growth is mainly driven by the ECEIW. The regional heterogeneity of the GUEIW is significant. The eastern region of China enjoys the highest GUEIW, while the central region suffers the poorest performance in the GUEIW. The western region has the largest internal gap of the GUEIW. The actual prices of industrial water in all the provinces are much lower than the shadow ones, and appropriate increase in the industrial water price is helpful to raise the GUEIW. Some policy implications are also suggested.

1. Introduction

China's urban industrial economy has achieved remarkable progress since the reform and opening up policy in late 1970s. As an important input in the industrial production, the amount of industrial water consumption has shown an obvious rising trend. As shown in Fig. 1, the total amount of industrial water in China shows an upward trend in 2004–2012, and it is as high as 142.2 billion tons in 2012. The water use efficiency in China's industry sector is relatively low, and millions of tons of water is wasted in the process of industrial production in recent years (Deng et al., 2016). On the other hand, water pollution caused by industrial production has posed great threat to people's health. We can find in Fig. 1 that the amount of industrial wastewater discharge is up to 24.66 billion tons, and it shows a slight decrease trend since 2007. Specifically, in 2012, the amounts of chemical oxygen demand (COD) and ammonia nitrogen (AN) in industrial wastewater are 3.38 and 2.64 million tons, respectively. Unfortunately, most of them are directly discharged into the water supply sources, which made almost each province in China experience accidents of river and lake pollution. It is well known that China is a nation with a serious water shortage problem, and the amount of water available per capita is only about a quarter of the world average level in 2012 (Wang et al., 2015). The awful waste of water and frequent water pollution incidents has made the problem of water shortage more severe, causing great negative impacts on social and economic development (Cheng et al., 2009; Xie and Wang., 2015a; Cai et al., 2016). Therefore, improving the water use efficiency and abating water pollution are critical for sustainable water use in China (Gao et al., 2014; Liu et al., 2014; Hu et al., 2016; Tu et al., 2015).

Fortunately, the central government of China is now aware of the problems and prepared to solve them. To save the precious water as much as possible, the State Economic and Trade Commission announced that the annual growth rate and the total amount of industrial water in China should fall below 130 billion tons,

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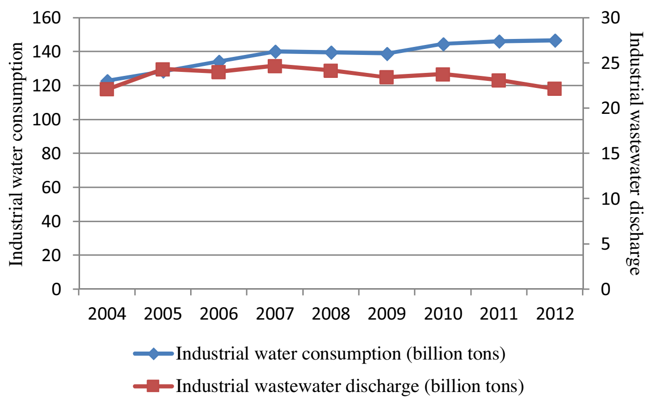

Fig. 1. Industrial water consumption and industrial wastewater discharge, 2004–2012 (http://nianjian.cnki.net/).

which accounts for less than 1.2% of the national water consumption during the 2001–2010.[1] In 2011, Chinese central government announced its most stringent water management plan known as the "3 Red Lines" water policy, which clearly stipulates the total amount of water consumption, the improvement of water use efficiency and water pollution treatment.[2] On the other hand, to deal with the problem of water pollution, the National People's Congress Standing Committee issued the *Law of Prevention and Control of Water Pollution* in 2008, which aimed at implementing strict regulation on industrial water pollution.[3] In addition, the Chinese State Council issued the "*Water pollution prevention action plan*" in April 2015, which consisted of a series of targets for water pollution regulation. In particular, the water quality in more than 70% of the seven major river basins in China should reach or exceed the class III standard by 2020, and this ratio should increase to 75% by 2030.[4] The industrial water use efficiency is expected to be greatly improved under those regulations (Cai, 2008). However, most of the policies from the central government are mainly based on the water use status of the whole country, which tend to ignore the regional heterogeneity. Actually, the characteristics of water use vary in different provinces, and appropriate and targeted countermeasures are necessary. For instance, since 2016, the Hebei Province has introduced a pilot policy namely "water resource tax" for Small and Medium-sized Enterprises. Therefore, it is extremely important to analyze the status of industrial water use at a regional level.

Additionally, as suggested by Kumbhakar and Bhattacharyya (1992), price plays an important role in determining the use efficiency of resource. Specifically, a relatively lower price can easily promote waste of water, and a relatively higher price of water may lead to higher production costs, which encourage producers to save water (Li and Ma, 2014). Thus, the price should be set within a reasonable range to achieve sustainable use of water. Unfortunately, the government has long determined the price of resource in China, and the water market can hardly play the role of setting reasonable prices and optimizing the allocations of resources. In particular, the local governments always tend to distort the price of water for their own interests, e.g., lowering the water price to attract more industrial investment, which could easily result in huge waste of water resource, and posing great threat to sustainable use of water resource (Fan and Mo, 2014). Therefore, how to calculate the reasonable price of water is a necessary and urgent issue.

Regarding the research methods for estimating the relative use efficiency of resources, many related recent studies would prefer distance function approach, which incorporates multiple input and output factors simultaneously (Zhang and Xie, 2015; Shao, 2016; Wu et al., 2014; Bian et al., 2014; Geissler et al., 2015; Jaeger and Rogge, 2014). There are two main methods to estimate the distance function, i.e., the nonparametric data envelopment analysis (DEA) approach and the parametric approach. The DEA approach, which is first proposed by Charnes et al. (1978), has gained much popularity in recent studies (Ren et al., 2013). A major advantage of the DEA approach over the parametric method is that a specific functional form on the underlying technology is not required (Zhang et al., 2014a,b; Zhang and Choi., 2014; Ren et al., 2014). As for the studies on evaluating the water use efficiency in China, Hu et al. (2006) conducted a pioneer empirical analysis in a total-factor DEA framework to evaluate the water use efficiency at the country level, and they presented the concept of water adjustment amount to determine the optimal scale of water use. Liao and Dong (2011) applied a similar approach to evaluate the water use efficiency at a provincial level. However, these studies only consider the economic efficiency, which might be regard as partial analysis because they ignore the pollutants caused by industrial production (e.g., wastewater and greenhouse gases). Therefore, we should incorporate both of the desirable and undesirable outputs in the model, and we can call the efficiency computed from this model "green use efficiency" (Wang et al., 2016; Xie et al., 2016; Zhao et al., 2009; Manzardo et al., 2014). In addition, most previous studies tended to apply a radial DEA approach, which aimed at expanding the good outputs and the contracting the bad outputs at the same rate. This is inconsistent with the actual production activities, and it often leads to the case where many of the observations under evaluation have the same efficiency value of 1, making raking the observations quite difficult (Zhou et al., 2007). Moreover, as Zhang et al. (2014a) pointed out, many related studies applied cross-sectional data other than time-series data, and the studies based on cross-sectional data could be regarded as contemporaneous efficiency evaluations. It is obvious that production technologies of each year are always not the same, and results based on contemporaneous production technology may not be reasonable. To overcome the problems, Zhang et al. (2014a,b) proposed a global non-radial DDF (GNDDF) approach, which expanded the good outputs and the contracted the bad outputs at different rates, and enveloped all of the contemporaneous technologies over the study period.

Some studies have estimated the prices of resources mainly based on cost or revenue function. However, as Atkinson and Halvorsen (1984) suggested, the cost or revenue function is not suitable when incorporating undesirable output and imperfect markets of resources. There are two approaches to estimate the shadow prices of input or output factors, i.e., the parametric and nonparametric methods. With respect to the parametric approach, which often takes a translog from, is widely applied in the studies on estimating the shadow prices of inputs and undesirable outputs. Coggins and Swinton (1996) employed the output distance function to compute the shadow price of sulfur dioxide of coal-burning electric utility plants in Wisconsin, US. Lee (2005) proposed an input distance functions to measure the shadow price of US electric power. Lee and Jin (2012) estimate the shadow price of nuclear capital and thermal capital in Korea based on a similar approach. Lee and Zhang (2012) computed the shadow price of carbon dioxide (CO_2) for the Chinese manufacturing industries. As for the nonparametric methods, Choi et al. (2012) calculated the shadow price of carbon dioxide in China based on the dual model of DEA approach. At the regional level, Zhang et al. (2014b) estimated the shadow prices of wastewater, sulfur dioxide and soot in Poyang Lake Ecological Economic Zone in China using a similar model.

[1] http://www.gov.cn/gongbao/content/2001/content_60999.htm.
[2] http://www.gov.cn/zwgk/2012-02/16/content_2067664.ht.
[3] http://www.gov.cn/flfg/2008-02/28/content_905050.htm.
[4] http://env.people.com.cn/n/2015/0416/c1010-26854928.html.

Although there are many researches on the use efficiency and shadow price for resources, however, to the best of our knowledge, there is no study on analyzing the green use efficiency of industrial water (GUEIW) at the national and provincial levels in China. Therefore, we apply a relatively advanced global non-radial DDF (GNDDF) model incorporating bad outputs to calculate the GUEIW in China over 2004–2012. We further compute its two component indicators named the economic efficiency of industrial water (ECEIW) and the environmental efficiency of industrial water (ENEIW) to find which one is the main contributor for the growth of the GUEIW. Then we compute the shadow price of industrial water from the dual model of DDF, and explore the market-price bias of industrial water for each province (autonomous province and municipality) in China based on the shadow price and actual price of industrial water.

This paper contributes to the current studies by presenting an empirical analysis of the actual status of China's industrial water green use efficiency based on a GNDDF model. Secondly, we calculate the ECEIWs and ENEIWs at the national and provincial levels, in order to find which one is the main driver for the growth of GUEIW. Lastly, we compute the shadow prices of industrial water for each province and propose a market-price bias index to show how to adjust the industrial water prices. Based on the previous studies, we assume that the GUEIW, ECEIW and ENEIW for China would show rising trends over the study period because of the continuous efforts of the Chinese government in economic development and environmental protection (Tian et al., 2014). In addition, the performances of industrial use may vary among provinces due to obvious regional disparities in industrial development (Golley, 2002). The shadow prices of industrial water may be higher than actual ones of all the provinces.

The remainder of this paper is organized as follows. Section 2 introduces the GNDDF approach and materials. Section 3 presents the empirical results, and Section 4 concludes with some policy implications.

2. Methods and data

2.1. GNDDF (Global non-radial directional distance function)

The traditional directional distance function (DDF) proposed by Chambers et al. (1996) is extended by Chung et al. (1997) to evaluate the environmental efficiency, which has been a widely accepted method in solving the problems of resources and environment efficiency estimation. However, as shown in Eq. (1), the traditional DDF approach always assumes that we can expand the good outputs and reduce the bad outputs at the same rate, which is regarded as a radial measurement, and is not in line with the real production activities. Additionally, this method may overestimate the efficiency because of the slack (Zhang et al., 2016a,b), and may result in the case where most of the decision making units (DMU) under estimation have the efficiency values of 1, which makes it difficult to rank the DMUs (Zhou et al., 2007). To overcome this problem, a non-radial DDF approach is developed and widely used in the studies on resource efficiency evaluations, which can be expressed as Eq. (2) (Chang and Hu, 2010):

$$\vec{D}(x, y, b; g) = \sup\left\{\beta : \left((x, y, b) + g \times \beta\right) \in T\right\} \tag{1}$$

$$\vec{D}(x, y, b; g) = \sup\left\{w^T\beta : \left((x, y, b) + g \times diag\left(\beta\right)\right) \in T\right\} \tag{2}$$

where $w^T = (x, y, b)^T$ refers to the normalized weight vector with respect to the inputs (x), desirable outputs (y) and undesirable outputs (b). $g = \left(-g_x, g_y, -g_b\right)$ is a directional vector. $\beta = \left(\beta_x, \beta_y, \beta_b\right)^T$ represents a vector of scaling factors refer to the adjustment ratios of expands for desirable outputs and reductions for inputs and undesirable outputs, and they are nonnegative numbers. Thus, the inputs and outputs would have different adjustment ratios, which is more in line with the actual production. The symbol *diag* stands for diagonal matrices. The symbol T refers to the environmental technology possibility set as follows.

In this study, we assume that there are N provinces under estimation. Each province has inputs (x) to produce desirable outputs (y) and undesirable outputs (b). Therefore, the environmental technology possibility set $T_1(x)$ can be expressed as follows:

$$T_1(x) = \left\{ \begin{array}{l} (x, y, b)\,|xcanproduce(y, b),\ \sum_{n=1}^{N} x_n\lambda_n \le x, \\ \sum_{n=1}^{N} y_n\lambda_n \ge y,\ \sum_{n=1}^{N} b_n\lambda_n = b,\ \sum_{n=1}^{N} \lambda_n = 1,\ \lambda_n > 0,\ n = 1, \ldots, N \end{array} \right\} \tag{3}$$

where the $T_1(x)$ is assumed to satisfy the production function theory, which states that finite amounts of inputs can only produce finite amounts of outputs, and inactivity is possible (Färe and Grosskopf, 2005). Moreover, we impose weak-disposability assumptions on $T_1(x)$, which means the reduction of undesirable outputs comes at a cost. Considering that production technology will change during the study period, we impose the constraints of $\sum_{n=1}^{N} \lambda_n = 1$ into the function for the variable returns to scale (VRS). However, the values estimated base on the contemporaneous benchmark technology, and the technologies over years are obvious different. Thus, the values in different years cannot be compared with each other. In order to solve this problem, Oh (2010) proposed a global benchmark technology, which envelops all the contemporaneous benchmark technologies. The global benchmark technology can be expressed as the accumulation of each period: that is $T_G = T_1 \cup T_2 \cup \ldots \cup T_N$, and the global environmental technology possibility set $T_2(x)$ can be defined as follows:

$$T_2(x) = \left\{ \begin{array}{l} (x, y, b)\,|xcanproduce(y, b),\ \sum_{t=1}^{T}\sum_{n=1}^{N} x^t{}_n\lambda^t{}_n \le x,\ \sum_{t=1}^{T}\sum_{n=1}^{N} y^t{}_n\lambda^t{}_n \ge y, \\ \sum_{t=1}^{T}\sum_{n=1}^{N} b^t{}_n\lambda^t{}_n = b,\ \sum_{n=1}^{N} \lambda_n = 1,\ \lambda_n > 0,\ n = 1, \ldots, N;\ t = 1, 2, \ldots, T \end{array} \right\} \tag{4}$$

In our study, according to the previous studies and data availability, the input contains three major indicators of industrial water (WA), industrial labor (L) and industrial capital (K), which refer to the amount of water used for industrial production, the number of labor in industrial sectors and annual net industrial fixed asset, respectively. The desirable output refers to industrial GDP (Y), and the undesirable outputs refer to the amounts of chemical oxygen demand (COD) and ammonia nitrogen (AN), which are two major pollutants in industrial wastewater. In order to remove the diluting effects of industrial labor and industrial capital, we remove them from the objective function and constraints. Therefore, we can compute the *GUEIW* by solving the following global non-radial DDF model:

$$\vec{D} = \max\left(w_{WA}\beta_{WA} + w_Y\beta_Y + w_{COD}\beta_{COD} + w_{AN}\beta_{AN}\right)$$
$$s.t.\begin{cases} \sum_{t=1}^{T}\sum_{n=1}^{N}\lambda_n^t WA_n \le (1-\beta_{WA})WA_0, \sum_{t=1}^{T}\sum_{n=1}^{N}\lambda_n^t L_n \le L_0, \sum_{t=1}^{T}\sum_{n=1}^{N}\lambda_n^t K_n \le K_0, \\ \sum_{t=1}^{T}\sum_{n=1}^{N}\lambda_n^t Y_n \ge (1+\beta_Y)Y_0, \sum_{t=1}^{T}\sum_{n=1}^{N}\lambda_n^t COD_n = (1-\beta_{COD})COD_0, \\ \sum_{t=1}^{T}\sum_{n=1}^{N}\lambda_n^t AN_n = (1-\beta_{AN})AN_0, \beta_{WA}\ge 0, \beta_Y \ge 0, \beta_{COD}\ge 0, \beta_{AN}\ge 0, \\ n=1,2,\ldots,N; t=1,2,\ldots,T; \lambda_n^t \ge 0, \sum_{n=1}^{N}\lambda_n^t = 1, \end{cases} \tag{5}$$

where the superscripts 0 represents the province under evaluation. β_{WA}, β_Y, β_{COD} and β_{AN} are the adjustment ratios of industrial water, industrial GDP, the amounts of COD and AN. λ is a non-negative vector. The superscripts t and n refer to the year t in the study period, and the number of provinces in the sample. The province is located on the frontier of production if α_i, γ_k and β_j have zero values. According to previous studies, we set the four weight vectors as (1/3, 1/3, 1/6, 1/6) since we include two undesirable outputs. Thus, we can calculate the *GUEIW* and its two decompositions base on the flowing equations:

$$ECEIW = \frac{\left(1-\beta_{WA}\right)+\left(1-\beta_Y\right)}{2} = 1 - \frac{\beta_{WA}+\beta_Y}{2} \tag{6}$$

$$ENEIW = \frac{\left(1-\beta_{WA}\right)+0.5\times\left[\left(1-\beta_{COD}\right)+\left(1-\beta_{AN}\right)\right]}{2} = 1 - \frac{\beta_{WA}+0.5\times\left(\beta_{COD}+\beta_{AN}\right)}{2} \tag{7}$$

$$GUEIW = \frac{\left(1-\beta_{WA}\right)+\left(1-\beta_Y\right)+0.5\times\left[\left(1-\beta_{COD}\right)+\left(1-\beta_{AN}\right)\right]}{3} = 1 - \frac{\beta_{WA}+\beta_Y+0.5\times\left(\beta_{COD}+\beta_{AN}\right)}{3} \tag{8}$$

The DMU under estimation is efficient in the use of industrial water when the value of the *GUEIW* is equal to 1, and it is inefficiently whenever the *GUEIW* is less than 1. The *ECEIW* and *ENEIW* are the same case.

2.2. The shadow price of industrial water

In order to provide reasonable suggestions to adjust the actual price of industrial water, we can use the dual model of the DDF approach to compute the shadow price of industrial water for each province, and the dual form of Eq. (5) is as follows:

$$\begin{aligned} &\min v_m x_m - w_j y_j + r_k u_k \\ &s.t. v_m x_m - w_j y_j + r_k u_k \ge 0 \\ &v_m \ge \left[\frac{1}{X_1},\ldots,\frac{1}{X_m},\ldots,\frac{1}{X_M}\right] \\ &w_j \ge \left[\frac{1}{Y_1},\ldots,\frac{1}{Y_j},\ldots,\frac{1}{Y_J}\right] \\ &r_k \ge \left[\frac{1}{B_1},\ldots,\frac{1}{B_k},\ldots,\frac{1}{B_K}\right] \end{aligned} \tag{9}$$

where $v \in R^m$, $w \in R^j$ and $r \in R^k$ respectively refer to the dual variables of the inputs, desirable outputs and undesirable outputs, which can be solved by Eq. (9). The purpose of Eq. (9) is to minimize the virtual cost in industrial production, and when the province under evaluation is efficient in industrial water use, the virtual cost is at best zero. Additionally, the symbols $v \in R^m$ and $r \in R^k$ refer to the shadow prices of the inputs and undesirable outputs, which are non-negative numbers. $w \in R^j$ can be expressed as the marginal virtual income of the desirable outputs. We can assume that the absolute shadow price of the desirable outputs is equal to its market price (P^X), and the absolute shadow price of industrial GDP is equal to its market price (P^Y) which is converted into 1 US $ constant 2004. Then the relative shadow price of inputs (P^X) with regard to the desirable output (P^Y) can be expressed as follows:

$$P^X = 1USD \times \frac{v}{w} \tag{10}$$

Therefore, the reasonable prices can be obtained from Eqs. (9) and (10).

2.3. Data

Table 1 shows the descriptive statistics of the input and output variables. The data are sourced from *The China Environmental Statistics Yearbook (2004–2012)*, *The China Statistical Yearbook (2004–2012)* and *The China City Statistical Yearbook (2004–2012)*. The industrial capital and GDP are converted base on the 2004 price.

According to the regional disparities of the provinces across China, we divide the provinces across China into three groups, the eastern, central and western regions. The eastern region is composed of three municipalities (Beijing, Tianjin, and Shanghai) and nine coastal provinces (Hebei, Liaoning, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, Taiwan and Hainan). This region enjoys the highest level of industrial development in China, with advanced industrial production technology and most of the foreign industrial enterprises in the whole country. The industrial GDP in this region accounts for more than 55% of the national industrial GDP in 2012. The central region consists of eight inland provinces (Shanxi, Jilin, Heilongjiang, Anhui, Jiangxi, Henan, Hubei and Hunan). This region is the main base of heavy industry of China, which requires huge amount of energy supply and produces great amounts of pollutants. The western region is composed of one municipality (Chongqing), and eleven inland provinces and autonomous provinces (Inner Mongolia, Guangxi, Sichuan, Guizhou, Yunnan, Shaanxi, Gansu, Qinghai, Ningxia, Xinjiang and Tibet). This region covers more territory than the other two regions, however, industry sectors in this region is the least developed compared with the other two regions. Some provinces in this region have even faced serious problem of water shortage. Because the complete data over the study period cannot be obtained, Tibet and Taiwan are not included in our sample.

3. Empirical results

3.1. GUEIW and its decompositions

In this subsection, we first calculate the GUEIW based on the GNDDF model and NDDF model in order to do comparison. Secondly, the two decomposition indicators of the GUEIW named ECEIW and ECEIW are computed based on Eqs. (6)–(8). Then we explore the regional heterogeneity of these indicators.

From Fig. 2 we can see that the GUEIW values computed from the GNDDF model are always lower than those based on the NDDF model over the study period, with the average values of 0.656 and 0.771, respectively. This means that the GUEIW based on NDDF model is overestimated because it is based on the contemporane-

Table 1
Descriptive statistics of input and output variables, 2004–2012.

	Variable	Unit	Max	Min	Mean	Std.	Observations
Input	Industrial water	10^8 m^3	225.25	2.50	45.77	44.10	270
	Labor	10^4 person	562.81	4.71	145.25	116.51	270
	Capital	10^8 Yuan	23032.72	84.81	4455.71	4160.47	270
Desirable output	GDP	10^8 Yuan	11520	119.68	3019.17	2691.53	270
Undesirable output	COD	10^4 ton	69.35	0.33	15.33	11.92	270
	AN	10^4 ton	5.69	0.04	1.15	1.01	270

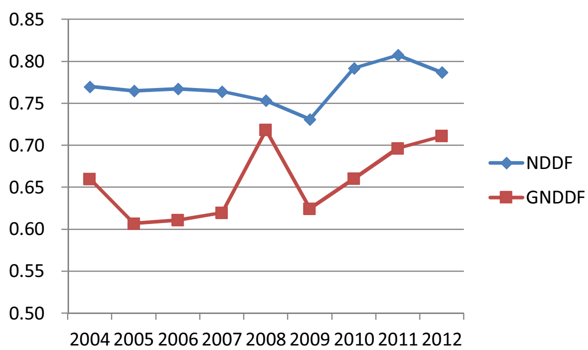

Fig. 2. Trends of the GUEIW for China based on GNDDF and NDDF models, 2004–2012.
Note: The GUEIW, ECEIW, and ENEIW represent the green use efficiency of industrial water, the economic efficiency of industrial water and the environmental efficiency of industrial water, respectively. GNDDF and NDDF refer to global non-radial directional distance function and non-radial directional distance function, respectively. The same as below.

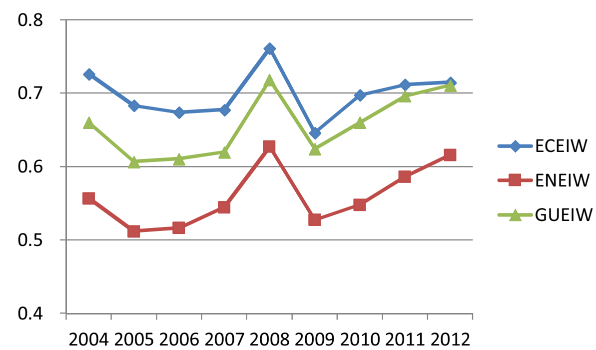

Fig. 3. Trends of GUEIW, ECEIW and ENEIW for China, 2004–2012.

ous environmental production technology. On the other hand, the value computed from GNDDF model is more reasonable, because the nodel is based on the global environmental production technology which envelops all the contemporaneous technologies in the study period. In addition, the trend of the GUEIW shows a W type curve, and it can be divided into two stages. The first one is from 2004 to 2008, and the second one is from 2009 to 2012. The trend of the first stage shows a U-type curve, with a decrease in 2005, and a continuous rising trend from 2006 to 2008. This indicates that the industrial water use had achieved obvious improvement during the three years. Unfortunately, a sharp decrease happened in 2009, and another rising trend can be found after 2009. Thus, we can see that the GUEIW in China has experienced several ups and downs over the study period. This is not consistent with the assumption in Section 1, which assume that the GUEIW shows a continuous upward trend, and this may due to the impacts of the ECEIW and the ENEIW. Thus, to provide further insight into the dynamic change of the GUEIW, it is necessary to analyze the trends of the two decompositions and find out which one is the main drive for the growth of the GUEIW.

Fig. 3 presents the trends of the ECEIW and the ENEIW, we can find that they share a similiar trend of the GUEIW. The ECEIW enjoys higher values than that of the ENEIW in each year over the study period, with the average value of 0.699, and the average value of ENEIW is only 0.556. This indicates that the growth of GUEIW is mainly driven by the ECEIW, and the environmental problem is an obstacle to achieve the green use of industrial water. This is consistent with Zhang et al. (2014a), and it is obvious that the environmental protection of the industrial sectors in China needs to be improved. In addition, it is worth noting that the ENEIW shows an obvious rising trend during 2006–2008 and 2010–2012, indicating an obvious environmental improvement happened in China. This is may be attributed to a series of laws and regulations such as the famous "Outline of China's water-saving technology policy" issued in 2005 which vigorously promoted the development of recycling water system in the industrial sectors, and the "water pollution prevention law" that were issued and revised during the 11th five year plan period (2006–2010) to strengthen the control of industrial pollutant emissions and encourage research and development into clean industrial production technology.[5] It is clearly that after a long period of rapid and extensive industrial development, the Chinese government has finally accepted the importance of environmental protection. Therefore, this result provides evidence for the Porter hypothesis (Porter and Van der Linde, 1995), which claims that stricter environmental regulations can stimulate technological innovation and improve production efficiency, leading to resource savings and environmentally friendly industrial production. However, the unanticipated international financial crisis happened in 2008 had brought serious negative impact on China's industrial exports, which caused many factories closed down and the workers lost their jobs. This forced the central government of China to introduce a series of economic stimulus plans, including expanding the scale of industrial investment across the whole country, in order to ensure the industrial economic growth, which resulted in the recovery of the ECEIW (Ouyang and Peng, 2015). On the other hand, under the economic stimulus plans, some heavy industry was overemphasized in most provinces across China, and the monitoring and implementation of environmental policy were temporarily suspected, which caused many rivers and lakes suffered serious industrial pollution (Zhang and Xie, 2015). Fortunately, the Chinese central government had timely recovered the normal development of economy, and restarted many environmental protection policies. Thus, the ENEIW value showed obvious increase after 2009.

At the provinceal level (Fig. 4), the eastern region enjoys the highest average GUEIW, ECEIW and ENEIW, with the values of 0.861, 0.795 and 0.887, respectively. The western region ranks second in the three regions, with the values of 0.576, 0.480 and 0.629, respectively. The central region shows the poorest performance in the three indicators, with the values of only 0.485, 0.331 and 0.538,

[5] Standing Committee of the National People's Congress. The people's Republic of China Water Pollution Prevention Law. Available online: http://www.gov.cn/flfg/2008-02/28/content_905050.htm.

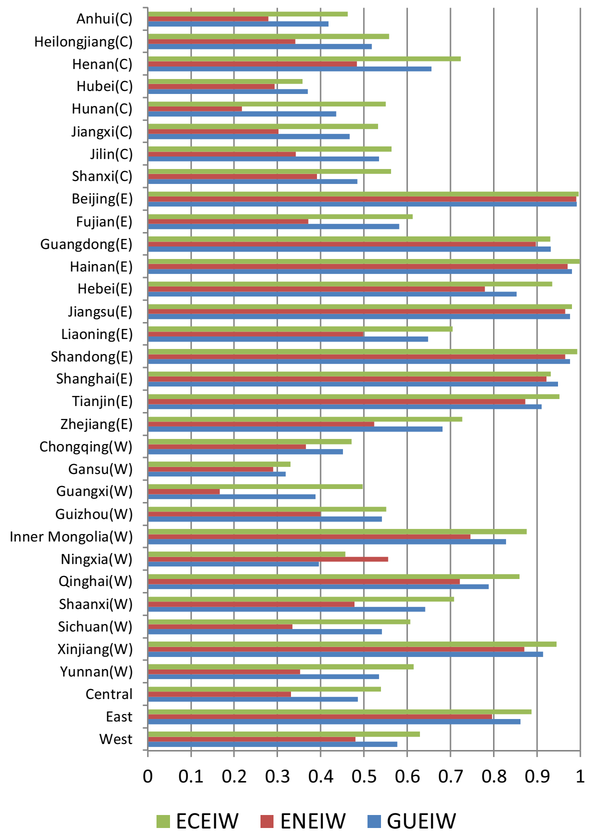

Fig. 4. Average values of ECEIW, ENEIW and GUEIW at the provincial level.

respectively. This is not consistant with the conclusions of Li and Ma (2014), which stated that the central region performed much better in green use of industrial water than that in the western region. A plausible reason may be that their results are based on contemporaneous environmental production technology, which is not suitable for comparison between the values of different years as we mention in Section 1.

At the provicial level, as shown in Fig. 4, Beijing enjoys the highest average GUEIW value of 0.991 over the study period, followed by Hainan with the average value of 0.982. It is worth noting that 7 out of the 8 provinces with the GUEIW values more than 0.9 are located in the eastern region of China (e.g. Beijing, Hainan, Jiangsu, Shandong, Shanghai, Guangdong, Tianjin and Hebei). The average value of the GUEIW in this region is 0.862 over the study period, which is much higher than those of the central and western regions, with the average GUEIW values of only 0.485 and 0.576, respectively. Additionally, out of 9 provinces whose average ECEIW values are more than 0.9, 8 are located in the eastern region (e.g. Beijing, Tianjin, Jiangsu, Zhejiang, Shandong and Hainan), and all the 5 provinces with the ENEIW values more than 0.9 are located in the eastern region of China (e.g. Beijing, Hainan, Jiangsu, Shandong and Shanghai). In contrast, most provinces from the central and western regions suffer poor performances of the three indicators. Thus, we can see that the eastern region shows better performance in industrial economic development and environmental protection, and this is consistent with the assumptions in Section 1, which states significant provinceal heterogeneity may exist. A plausible reason may be that the eastern region enjoys a more developed economy and obvious advantages of talents compared with the other two regions, which can well help achieve industrial structure transformation, and develop advaced production technology to achieve sustainablr use of industrial water. This is consistant with the conclusion of Ouyang and Fu (2012), which stated that

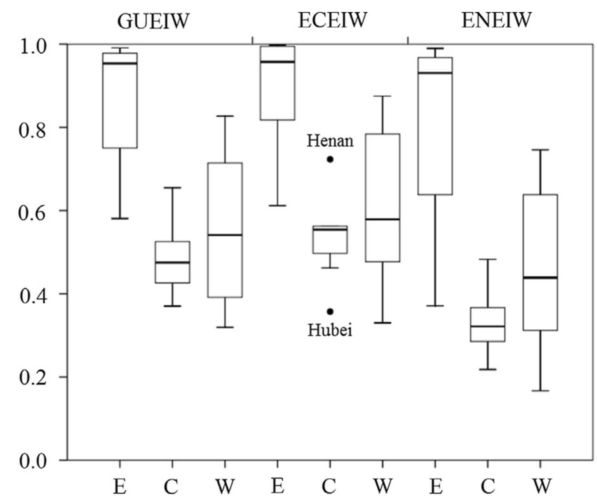

Fig. 5. Boxplots of ECEIW, ENEIW and GUEIW for the eastern, central and western regions in China.
Note: E, C, W represent the eastern, central and western China.

eastern provinces in China had achieved faster progress than the central and western provinces in the production technology. More importantly, the inter-regional spillover effect was obvious, which indicated that the provinces in eastern China had brought positive and significant effect on the growth of central and western provinces in industrial development. Therefore, this may be a good chance for the inland provinces with relatively less developed industrial production technology to learn from the eastern provinces (Ouyang and Fu, 2012).

In order to show detail information about the internal gaps in the GUEIW and its two decompositions within the three regions, we present the boxplots of the three indicators. As shown in Fig. 5, the central region has the smallest internal gap in the ENEIW and GUEIW, and it has the smallest internal gap in the ECEIW except for Henan and Hubei. Specifically, compared with those of other provinces in the central region, the value of ECEIW in Henan is too high while that in Hubei is too low. This indicates that the two provinces are quite typical compared to other central provinces in the ECEIW. This may because that Henan has aimed to introduce low polluting industrial enterprises in recent years. This policy has brought great economic benefits, and environmental damage is not that serious. However, as an important industrial base in China for a long time, the heavy industry is overemphasized including many industrial sectors with serious pollution problems, and this has caused serious environmental damage in Hubei (Ding, 2014). On the other hand, the western region suffers the greatest internal gaps in the three indicators. This may because that cooperation in industrial development is not enough, which call for more communication among the provinces in future. In addition, there is no other typical province for the other two indicators, which indicates the internal gaps in the two indicators are not that large.

In general, the GUEIW in China has experienced several fluctuations over the study period. Its growth is mainly driven by ECEIW, while the ENEIW appears to be a short board for achieving efficient performance in industrial water use. The eastern region shows better performances in all the three indicators than the central and western regions, especially in the ENEIW. Considering the eastern region in China enjoys most developed economy, and per capita income is much higher than that of the central and western regions. Therefore, the result provides support for the hypothesis of Kuznets curve, which states that people would pay more attention to environmental protection and improve the use efficiency of resource after their income exceeds a certain level (Li et al., 2016). Thus, the central and western provinces should focus on economic devel-

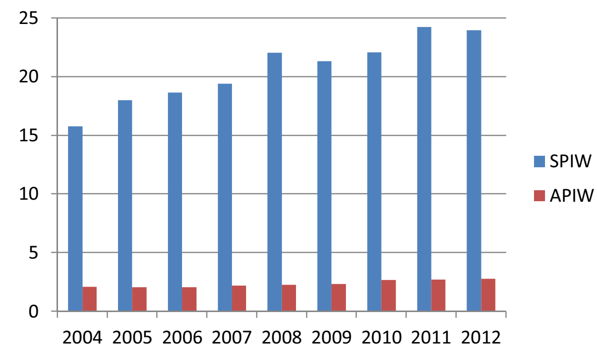

Fig. 6. The average SPIWs and the APIWs at the national level in China, 2004–2012. *Note:* SPIW represents the shadow price of industrial water; APIW represents the actual price of industrial water. The same as below.

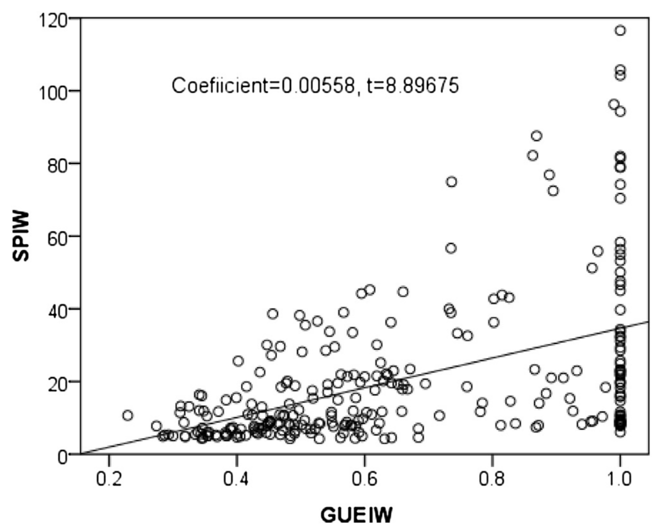

Fig. 7. Relationship between the GUEIW and the SPIW.

opment as well as the environmental protection, and it would be a wise choice to develop appropriate industries with less pollution and high output (Xie and Wang, 2015b). Additionally, internal gaps in the GUEIW are quite significant and deserve more attention. To achieve balanced and sustainable industrial water use, China's central government needs to take effective countermeasures, such as strengthening supervision of local government to implement the environmental protection policies, and encouraging the eastern provinces to provide necessary technical and financial support for the provinces with relatively low GUEIWs.

3.2. Shadow prices of industrial water (SPIW)

In this section, we calculate the shadow prices of industrial water base on Eqs. (9) and (10) for each province in China over the sample period. As shown in Fig. 6, the average SPIWs for China are much higher than the average actual prices of industrial water (APIW) in each year over the study period. This indicates great bias between the SPIW and the APIW. At the provincial level (Table 2), we can note that Tianjin has the highest SPIWs for most years of the sample period, and the SPIW is as high as 16.6 US $ per cubic meter in 2012. Shandong and Beijing also have relatively higher SPIWs than those of other provinces, with the SPIWs of 11.21 and 9.29 US $ per cubic meter. Xinjiang has the lowest SPIW of only 0.77 US $ per cubic meter. Fig. 7 presents the relationship between the GUEIW and the SPIW. We can find that there is a significant positive relationship between them, which indicates that an increase in SPIW would help raise the GUEIW.

In order to represent the actual water pricing performance of each province, as Eq. (11) shows, we define the water pricing performance index (WPPI) as the difference between estimated shadow price and real purchasing price of industrial water to measure the current price bias based on the market mechanism. Because the shadow price refers to the marginal cost of the industrial water, the shadow price would be greater than zero since the input of water is necessary in industrial production. The value of WPPI has an upper bound of unity, which would occur if the APIW is equal to zero. However, this is not reasonable in practice and it is never reached. In addition, the WPPI is bounded from below by 0 which occurs if the APIW is less than SPIW, and the WPPI will be below zero whenever APIW is greater than SPIW. Fig. 8 shows WPPI for each province in 2012.

$$WPPI = 1 - \left(\frac{APIW}{SPIW}\right) \tag{11}$$

As shown in Fig. 8, we can find that the WPPI values of each province are greater than 0, indicating that the SPIW values in all the provinces are higher than APIW values. Specifically, 10 of all the 30 provinces in our samples are painted red, and they have the WPPI values lie between 0.9 and 1, which means that the SPIWs for these provinces are more than 10 times the APIWs (e.g. Shandong, Qinghai and Shaanxi). Shangdong suffers the largest WPPI value of 0.959, indicating that the SPIW is about 24 times as much as the APIW. Qinghai and Shaanxi rank second and third with the WPPI values of 0.956 and 0.943, which means the SPIWs in the two provinces are around 23 and 18 times as much as the APIWs. This indicates ridiculous gaps between the shadow prices and the actual ones in these provinces. A plausible reason may be that most of these provinces are facing the problems of water shortage and overpopulation. This is especially for Beijing and its surrounding provinces, which is known as the political and financial center of China, has been suffering the problem of water shortage for a long time. Although the central government of China has tried many ways to solve the problem, such as the famous project named "the South-to-North Water Diversion", the results are unsatisfactory (Chen and Wang, 2012). In fact, the APIWs in these provinces are around 0.64 US $ per cubic meter, which are only a little higher than those of the provinces with relatively richer water resource (e.g. Hunan and Guangxi), with the prices about 0.5 US $ per cubic meter, making it difficult to improve the consciousness of the people to save water. Additionally, the reason why Xinjiang and Qinghai have relatively higher WPPIs might be that most regions of these two provinces are filled with the desert, and water is very limited and precious (Thevs et al., 2015). This is the similar case with Shaanxi. Zhejiang is the only one province painted red in southern China, and this may because that the APIW is too low, which is only 0.27 US $ per cubic meter in 2012. Thus, provinces in the red region need to raise the APIWs greatly raised.

The WPPIs of provinces in the blue region lie between 0.80.9, indicating that the SPIWs for these provinces are 5–10 times as much as the APIWs. Some provinces are located in southern China, which enjoy relatively richer water resource (e.g. Guangdong and Jiangsu), this is may be the reason why they are not facing serious water shortages though huge industrial water consumptions exist. Several provinces in northern China (e.g. Inner Mongolia, Ningxia and Shanxi) and Sichuan in southwestern China are also painted blue, this may because that scales of industrial development in these provinces are relatively small than the economically developed provinces, and focused on light industry sectors with less pollution. The provinces painted yellow have the WPPIs between 0.5 and 0.8, which indicates the SPIWs for these provinces are 1–5 times as much as the APIWs. These provinces are mostly located in

Table 2
The SPIW values for each province of China, 2004–2012.

Province	Region	2004	2005	2006	2007	2008	2009	2010	2011	2012
Beijing	E	9.03	11.93	13.09	13.95	18.57	15.33	15.02	16.84	16.60
Tianjin	E	8.75	12.55	12.96	12.24	13.06	12.60	11.55	11.82	11.21
Hebei	E	5.36	7.17	7.43	7.97	8.46	8.16	8.97	8.90	9.29
Liaoning	E	2.72	3.46	4.01	4.80	5.12	5.65	6.21	7.21	7.12
Shanghai	E	4.54	4.72	4.49	4.70	5.47	5.33	5.78	6.37	6.97
Jiangsu	E	5.17	5.19	5.29	5.78	6.32	6.20	6.81	7.58	6.86
Zhejiang	E	3.60	4.34	4.08	4.79	5.82	6.15	6.08	7.04	5.37
Fujian	E	0.97	0.93	0.96	1.06	1.13	2.90	3.09	3.66	4.95
Shandong	E	3.11	3.21	3.00	3.46	3.72	3.96	4.09	4.68	4.55
Guangdong	E	3.07	3.12	3.06	3.12	3.40	3.50	3.48	3.66	3.49
Hainan	E	3.06	3.05	3.16	3.22	3.72	3.41	3.53	3.73	3.43
Shanxi	C	2.96	3.35	3.64	3.35	3.67	2.85	3.17	3.59	3.18
Jilin	C	1.87	2.23	2.33	2.33	2.52	2.45	2.54	2.64	2.93
Heilongjiang	C	2.20	2.07	2.19	2.45	2.79	2.38	2.47	2.80	2.85
Anhui	C	1.22	1.27	1.38	1.46	1.71	1.70	1.94	2.25	2.67
Jiangxi	C	1.84	1.89	2.11	2.38	2.95	2.61	2.56	2.96	2.48
Henan	C	1.25	1.41	1.46	1.31	1.31	1.42	1.65	1.86	1.89
Hubei	C	1.15	1.24	1.39	1.67	1.87	1.70	1.92	2.09	1.82
Hunan	C	0.95	0.89	0.81	0.85	0.89	1.13	1.28	1.47	1.75
Inner Mongolia	W	1.69	1.39	1.34	1.27	1.37	1.17	1.35	1.49	1.74
Guangxi	W	1.88	1.83	1.90	1.69	1.86	1.71	1.68	1.75	1.71
Chongqing	W	1.35	1.28	1.28	1.27	1.44	1.56	1.65	1.73	1.71
Sichuan	W	1.36	1.28	1.25	1.21	1.26	1.22	1.29	1.40	1.56
Guizhou	W	0.80	0.80	0.86	0.96	1.02	0.98	1.15	1.31	1.42
Yunnan	W	0.68	0.81	0.90	0.86	0.93	1.11	1.23	1.40	1.37
Shaanxi	W	1.43	1.45	1.51	1.43	1.46	1.18	1.27	1.27	1.35
Gansu	W	0.74	0.78	0.83	0.90	1.04	1.06	1.15	1.35	1.29
Qinghai	W	0.87	0.77	0.70	0.72	0.82	0.80	0.94	1.12	1.12
Ningxia	W	1.00	0.84	0.85	0.79	0.89	0.95	0.94	1.09	1.11
Xinjiang	W	0.68	0.72	0.79	0.70	0.74	0.68	0.73	0.79	0.77

Unit: US $ per cubic meter.

the central and western regions of China with relatively low GUEIW. Therefore, APIWs of provinces in the blue and yellow regions need moderate increase.

The only one province painted grey is Guizhou, with the WPPI value of 0.484, which indicates the SPIW is about 1.9 times as much as the APIW. This may because that scale of industrial development is relatively smaller in Guizhou compared with that of most provinces in China, which results less water for industrial production. Actually, the industrial GDP in Guizhou is relatively low, which only accounts for around 1.1% of the national industrial GDP, and much less than that of some developed provinces such as Guangdong (12.93%) and Jiangsu (11.97%).[6] In addition, Guizhou has done a good job in environmental protection in recent years, and it is famous for tourist attractions with beautiful mountains and rivers. (Shang et al., 2014). However, the local government has shown a strong interest in industrial development, and a series of polices aiming at achieving a vigorous development in industry in recent years, especially for the heavy industry sectors. This would inevitable result in a huge water demand. Therefore, a moderate increase in the APIW may help improve the GUEIW by increasing the production cost to force producers to save water.

In a word, the actual prices of industrial water in all the provinces across China are lower than the shadow ones, and they need appropriate increases. The provinces enjoy rapid industrial development and less water should greatly increase their APIW values to alleviate water shortage, and those with relatively richer water should make moderate increase in the prices. More importantly, in order to realize the function of price optimizing allocation and utilization of industrial water, the power of determining the price should be returned to the market rather than hold by the local government.

4. Conclusions and policy implications

As the water shortage and industrial water pollution have posed great threat to sustainable water use in China, it is an urgent work to estimate the state of green use efficiency of industrial water (GUEIW), and provide some useful policy recommendations. Based on a global non-radial DDF model, this paper computes the GUEIWs for 30 provinces in China during 2004–2012 as well as its two decomposition indicators (i.e., the ECEIW and the ENEIW). We then compute the shadow prices of industrial water based on the dual model of DDF at the provincial level, and analyze the bias between the actual price and the shadow ones for each province.

The empirical results show that the GUEIW shows several fluctuations over the study period and most provinces in China have not achieved performed efficiently in industrial water use. The ECEIW is the main contributor of the growth of GUEIW. Thus, the environmental protection in the process of industrial production deserves more attention. The eastern region of China enjoys better performance in the GUEIW and its two decomposition indicators than those in the central and western regions. Regarding the provincial heterogeneity, the provinces in the central region show the least internal gaps in the GUEIW, while those in the western region suffer the largest internal gaps. The shadow prices of industrial water are much higher than the actual ones in all the provinces, and an appropriate increase of industrial water prices would result in obvious improvement of GUEIW.

We can put forward some policy implications based on the empirical results. To improve the economic efficiency of industrial water, we should develop or introduce advanced water use technology to make full use of water resource in the industrial production, and provinces enjoy advanced technology should help provinces with less developed technology to achieve balanced development of industrial water use. In addition, to encourage industrial producers to save water, the government can provide subsidies to the

[6] http://www.stats.gov.cn/tjsj/ndsj/2013/indexch.htm.

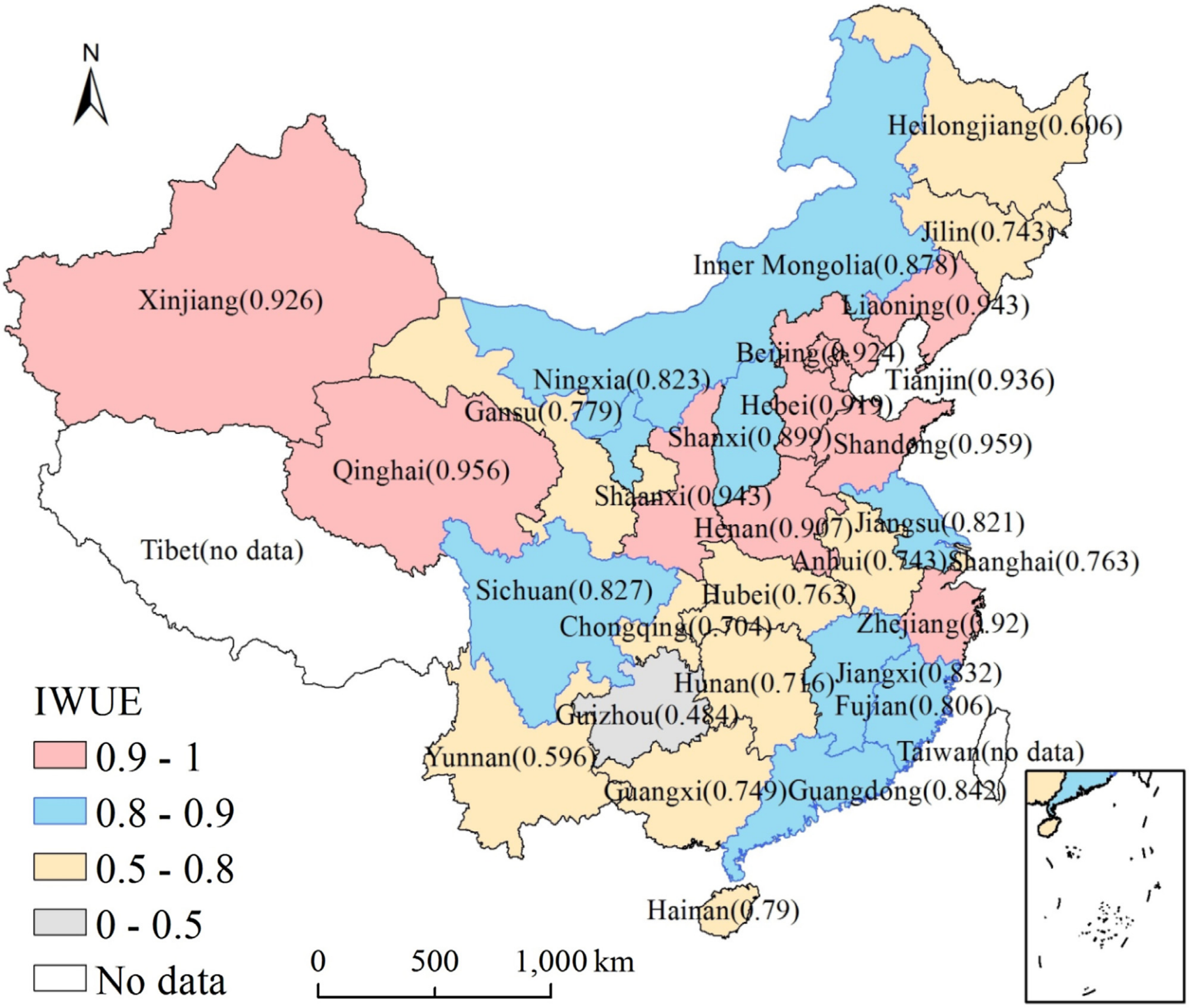

Fig. 8. The WPPI value for each province of China, 2012. *Note:* WPPI represents the water pricing performance index.

producers with outstanding performance in saving water. Moreover, the application of multistep water price, which means that the water price would increase with the increase of water consumption, may help save water resource and raise the water use efficiency, especially in provinces with relatively high WPPI values.

To raise the environmental efficiency of industrial water, the central government of China should carry out more strict regulations to deal with the problem of water pollution. Considering that local government officials often lack of motivation to implement policies out of their own benefit, the central government should severely punish illegal officials and remove them from their positions. Additionally, equipment and technology for processing industrial wastewater should be developed or introduced as soon as possible, and the industrial producer tend to adopt environmentally friendly production technology should be given incentives and subsidies. Lastly, industrial wastewater needs to be treated carefully by physical or chemical methods, and it can be discharged into the natural environment after passing through the examinations by the environmental authorities.

There are also some limitations in this study. For instance, our empirical analysis is based on data only for the 2004–2012 periods, and a longer period would help improve the accuracy of empirical analysis. Additionally, we have only selected the amounts of chemical oxygen demand and ammoniac nitrogen in industrial wastewater as environmentally undesirable outputs, and some other pollutants (e.g., phosphorus and heavy metals) are not considered, which mainly due to the unavailability of data. In addition, factors from the humanistic aspect such as human capital are not included in this study for the same reason, and we will make improvements in further studies to provide more convincible empirical results.

Disclaimers

The authors declare no competing financial interest. The views expressed in the article are personal and do not necessarily reflect an official position of the European Commission.

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