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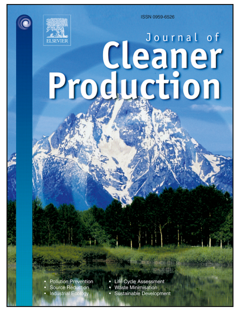

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Industrial Water-Use Efficiency in China: Regional Heterogeneity and Incentives Identification

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Industrial Water-Use Efficiency in China: Regional Heterogeneity and Incentives Identification

Abstract: Progress has been made in improving water-use efficiency (WUE) in China, whereas problems such as unbalanced regional and industrial WUE development still exist. In this study, the WUE of 30 provinces in mainland China at the overall level as well as three industrial (i.e., primary, secondary, and tertiary industrial) levels are investigated. The study covers the time period 2005 to 2015 and is based on the Slacks-based measure approach combined with the Super-efficiency model dealing with undesirable outputs; in addition, a multidimensional analytical framework was developed in this study. Afterwards, the geographical detector model is applied to identify the driving forces of WUE, serving as a reference for policies and strategies needed to improve WUE. Results indicate that China's overall WUE has been improving since 2005, though further progress is necessary. At the regional level, five regions (i.e., water abundance, vulnerability, stress, scarcity, and absolute scarcity) grouped by the availability of water resources per capita are all the most efficient in terms of water use in the primary industry. The absolute scarcity region performs best in all four dimensions despite the scarcity of water resources per capita, yet the water stress region has the lowest WUE. At the provincial level, provinces in the eastern coastal region, especially the south-eastern coastal region, have the highest WUE, whereas those in the interior south-eastern and south-western region have the lowest. Industrial structure, research and development intensity, and higher education are the main driving forces of WUE. Their mutual interactions and their interactions with other indicators are highly influential.

Keywords: Water-use efficiency; Regional analysis; Inter-industry comparison; Data Envelopment Analysis; Undesirable outputs; China

Nomenclature

WUE	water-use efficiency	n	the number of DMUs
DEA	data envelopment analysis	m	the number of inputs
DMU	decision making unit	p_1	the number of desirable outputs
CRS	constant return to scale	p_2	the number of undesirable outputs
VRS	variable return to scale	$\boldsymbol{x}$	input vector
SBM	slacks-based measure	$\boldsymbol{y}$	desirable output vector
USBM	SBM approach dealing with undesirable outputs	$\boldsymbol{z}$	undesirable output vector
Super-USBM	USBM approach combined with the Super-efficiency model	X	input matrix
AN	ammonia nitrogen	Y	desirable output matrix
ANE	AN emission	Z	undesirable output matrix
COD	chemical oxygen demand	$\boldsymbol{\lambda}$	weighting vector
CODE	COD emission	$\boldsymbol{s}^-$	input slacks vector
GRP	gross regional product	$\boldsymbol{s}^g$	desirable output slacks vector

TIFA	total investment in fixed assets	s^b	undesirable output slacks vector
TNEP	total number of employed persons	ρ^*	optimal solution of USBM model
TWU	total water use	α^*	optimal solution of Super-USBM model
IS	industrial structure		
PS	population structure	σ^2	statistical variance
R&D	research and development	E_i	efficiency value of DMU_i
RDII	R&D input intensity	SST	total sum of squares
RDP	R&D personnel	SSW	within sum of squares
HTP	high-tech production	PI	the primary industry
EF	educational funds	SI	the secondary industry
HEG	higher education graduates	TI	the tertiary industry
PPS	production possibility set	m^3	cubic meter

1. Introduction

Unreasonable water use can place constraints on ecosystem health, socioeconomic development, and even human survival[1]. To enhance water-use efficiency (WUE) and further sustainable development, the United Nations General Assembly declared the period from 2018 to 2028 as the International Decade for Action "Water for Sustainable Development"[2]. WUE has also drawn widespread attention from academia. Academic research on sustainable water use emerged in the late 1990s. The percentage of literature using WUE as one of the keywords increased from 4.31% in 1998–2007 to 11.53% in 2008–2017 (Aznar-Sánchez et al., 2018). Efficiency-related variables also become the most commonly used variables in this field (Azad et al., 2015; Bian et al., 2014; Cruz et al., 2013; Long and Pijanowski, 2017; Zhang et al., 2016), accounting for a share of 35.57% (Aznar-Sánchez et al., 2018).

China is facing water-use problems. Particularly, the low level of processing water resources per capita is a key concern. The country's water resources per capita cover only 2100 cubic meters, equal to 28% of the global average level (Ministry of Water Resources PRC, 2012)[3]. Other problems such as unbalanced distribution of regional water resources and reduction of total water resources are also evident. According to the World Resources Institute (2019), more than half of China's provinces are suffering from water scarcity, while two thirds of China's cities face critical water shortages, and nearly one third of China's ten major river systems are of poor water quality[4]. The government has been responding to counter these concerns. For instance, the *Law of Prevention and Control of Water Pollution* has been set as its objective preventing and controlling water pollution as well as protecting water ecology to realize sustainable development. The *Law of Water and Soil Conservation* was legislated to incorporate water conservation into the national economic and social development plan. Progress has been made with these efforts, yet WUE in China still needs enhancement, which is regarded as an important means to realize and promote sustainable development in the environment, economy, and society (Suzuki and Nijkamp, 2016).

Understanding the current status of WUE is one of the prerequisites for improving it. Therefore, this study aims to investigate the WUE in mainland China. In social science, WUE is also called economic WUE, defined as the value of products produced per unit of water consumption (Wang et al., 2015). Studies have been conducted following this conceptual framework (Azad et al., 2015; Bouman, 2007; Huang et al., 2005). It was later recognized that water alone as an input cannot produce the necessary outputs in the production process. Other inputs are also essential in WUE assessment (Hu et al., 2006). Therefore, studies on total factor WUE measured by multiple-input models come into the mainstream.

Data Envelopment Analysis (DEA) is one of the most widely used methods for its ability to deal with multiple inputs and outputs. First proposed by Charnes et al. (1978), conventional DEA models, such as the Charnes–Cooper–Rhodes or

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[1] https://www.un.org/en/sections/issues-depth/water/index.html
2 https://www.un.org/en/events/waterdecade/
[3] http://news.china.com.cn/txt/2012-02/13/content_24625293.htm
[4] http://www.wri.org.cn/en/our-work/topics/water

Banker–Charnes–Cooper model, are the most popular (Frija et al., 2009; Geng et al., 2019; Lombardi et al., 2019; Razzaq et al., 2019). However, such models with radial and oriented features neglect excesses in inputs and shortfalls in outputs (Tone, 2001) that are likely to deviate the efficiency measurement. Hence, the efficiency assessed by traditional DEA may not accurately reflect real efficiency level of decision making units (DMUs). To counter this issue, non-radial and non-oriented DEA models are proposed, among which slacks-based measure (SBM) applied (Azad et al., 2015; Chen et al., 2018; D'Inverno et al., 2017; Wu et al., 2018; Chen et al., 2019a).

Conventional SBM-DEA models fail to fully rank DMUs. Consequently, studies applying this method can only focus on inefficient DMUs, impeding the investigation of all DMUs in the whole region (for example, mainland China analyzed in this study). Furthermore, only economic efficiency was evaluated when measuring WUE, represented by the consideration of desirable outputs but the neglect of undesirable outputs. Recently, it was noticed that pollutants also need to be accounted for they are inevitably produced and further discharged in the production process, signaling the importance of environmental efficiency assessment of water-use. Therefore, with cleaner production taken into consideration, researchers started to evaluate WUE with undesirable outputs included (Bian et al., 2014; Deng et al., 2016; D'Inverno et al., 2018; Frija et al., 2009). Nonetheless, these studies are still in the minority.

From the perspective of research objective, related literature can be divided into three broad themes: industrial WUE (especially agriculture and irrigation), water utility WUE, and overall WUE. In the first theme, WUE of one industry or sector is frequently assessed. Studies on WUE in agriculture, especially irrigated agriculture (Azad et al., 2015; Watto and Mugera, 2019), investigate the efficiency in water management and are especially prevalent. Other studies focus on the assessment of industrial WUE (Chen et al., 2018), infrastructure intensive agencies (Woodward et al., 2019), and the water sector (Cruz et al., 2013). In the second theme, the studies focus on water utilities or water treatment plants to assess WUE (Castellet and Molinos-Senante, 2016; D'Inverno et al., 2017; Zhou et al., 2018), with results ranging from efficient performance to complete inefficiency. In the third theme, regional analyses based on various data levels is common; these types of studies also account for the largest share between the three themes. Some studies focus on provincial level data (Bian et al., 2014; Byrnes et al., 2010; Deng et al., 2016; Wang et al., 2015; Yao et al., 2018), while others focus on city level analyses (Gungor-Demirci et al., 2018; Morales and Heaney, 2016).

It can be concluded that previous studies focus more on WUE of a certain industry or at the overall level, owning shortcomings in two aspects. On the one hand, investigating the WUE of one industry cannot reflect the efficiency level of this industry among all industries in the region. On the other hand, examining overall WUE alone fails to identify the advantaged and disadvantaged industries in this region, hindering the in-depth understanding of regional WUE. Consequently, an inter-industry WUE analysis is essential in addition to the assessment of regional WUE at the overall level.

The purpose of this study is to investigate regional WUE and its driving forces in mainland China. Thirty provinces in mainland China (excluding Tibet, which has missing data) are taken as DMUs. This paper advances existing literature in two ways. First, a multidimensional analytical framework is constructed, based on which China's regional WUE at the overall and industrial (i.e., primary, secondary, and tertiary industrial) levels are analyzed. Second, the SBM approach combined with the Super-efficiency model dealing with undesirable outputs (thus, Super-USBM model) are developed for efficiency assessment and full ranking of all DMUs. Undesirable outputs are also considered, so that both economic and environmental efficiency of water-use can be accounted. In this study, three input indicators (labor, assets, and water consumption), one desirable output indicator (economic output) and two undesirable output indicators (ammonia nitrogen emissions and chemical oxygen demand emissions) are selected for measurement. Furthermore, a geographical detector model is applied to identify the driving forces of WUE, serving as reference for policy and strategy improving WUE. Following previous literature, WUE in this paper is the total factor WUE. Scopes of the three industries are given by the Statistical Yearbook of China. The primary industry includes agriculture, forestry, animal husbandry, fishery, and water conservancy. The secondary industry includes industry, mining, manufacturing, electric power, gas and water production and supply. The tertiary industry includes all industries with the exception of primary and secondary industries such as transport, storage, post, wholesale and retail trades, hotels and catering services, and household consumption.

The remaining paper is organized as follows: Section 2 presents the Super-USBM model used in this paper for calculating regional WUE and the geographical detector model for identifying the driving forces. Section 3 analyzes regional WUE in China and identifies the driving forces of WUE. Section 4 concludes and proposes policy implications.

2. Methodology

In this study, a two-part methodological framework is employed to investigate China's regional WUE and its driving forces. First, a Super-USBM model is developed to assess regional WUE in China. Second, the driving forces of WUE in different regions are identified by a geographical detector model.

2.1 Super-USBM model

Conventional DEA models are radial and oriented, referring to an efficiency evaluation based on a certain proportion of input and output and input or output orientation. Nonetheless, there often exists a redundancy in the input or an insufficiency in the output during the production process, which traditional DEA models neglect. In this case, the non-radial and non-oriented measurement SBM model that considers both inputs excesses and outputs shortfalls (called slacks) can better measure the efficiency of DMUs by eliminating errors caused by radial and oriented methods (Tone, 2001).

Consider n DMUs with m inputs, p_1 desirable outputs and p_2 undesirable outputs. Denote the input and output vectors as $\boldsymbol{x}, \boldsymbol{y}, \boldsymbol{z}$, then the input and output matrices can be defined as X, Y, Z, where $X, Y, Z > 0$. The production possibility set (PPS) reflecting all the outputs produced by m inputs under the assumption of constant return to scale (CRS) is

$PPS = \{(\boldsymbol{x}, \boldsymbol{y}, \boldsymbol{z}) \mid \boldsymbol{x} \geq X\lambda, \boldsymbol{y} \leq Y\lambda, \boldsymbol{z} \geq Z\lambda, \lambda \geq 0\}$, where λ is a weighting vector in R^n. Under the assumption of variable return to scale (VRS), λ should also meet the constraint $\sum_{j=1}^{n} \lambda_j = 1$.

For $\text{DMU}(\boldsymbol{x}_o, \boldsymbol{y}_o, \boldsymbol{z}_o)$, the SBM model dealing with undesirable outputs (Tone 2004) can be measured as:

$$
\begin{aligned}
\rho^* = \min \ & \frac{1 - \frac{1}{m}\sum_{i=1}^{m} \frac{\boldsymbol{s}_i^-}{x_{io}}}{1 + \frac{1}{p_1 + p_2}\left(\sum_{r=1}^{p_1} \frac{\boldsymbol{s}_r^g}{y_{ro}^g} + \sum_{r=1}^{p_2} \frac{\boldsymbol{s}_r^b}{y_{ro}^b}\right)} \\
s.t. \quad & \boldsymbol{x}_o = X\boldsymbol{\lambda} + \boldsymbol{s}^- \\
& \boldsymbol{y}_o^g = Y^g\boldsymbol{\lambda} - \boldsymbol{s}^g \\
& \boldsymbol{y}_o^b = Y^b\boldsymbol{\lambda} + \boldsymbol{s}^b \\
& \sum_{j=1}^{n} \boldsymbol{\lambda}_j = 1 \\
& \boldsymbol{s}^-, \boldsymbol{s}^g, \boldsymbol{s}^b, \boldsymbol{\lambda} \geq 0
\end{aligned}
, \qquad (1)
$$

where $\boldsymbol{s}^-$, $\boldsymbol{s}^g$ and $\boldsymbol{s}^b$ are the slacks of input, desirable outputs and undesirable outputs, respectively. The optimal solution of this fractional program is $(\rho^*, \boldsymbol{\lambda}^*, \boldsymbol{s}^{-*}, \boldsymbol{s}^{g*}, \boldsymbol{s}^{b*})$ and ρ^* is the efficiency index of DMU_o. The value of ρ^* range from 0 to 1. DMU_o is considered SBM-efficient if $\rho^* = 1$.

Super-USBM model (Andersen et al., 1993; Tone, 2002) is further developed for ranking the SBM-efficient DMUs[1]. For the SBM-efficient DMU_k, the objective function model of Super-USBM can be described as:

$$
\begin{aligned}
\alpha^* = \min \ & \frac{1 + \frac{1}{m}\sum_{i=1}^{m} \frac{\boldsymbol{s}_i^x}{x_{ik}}}{1 - \frac{1}{p_1 + p_2}\left(\sum_{r=1}^{p_1} \frac{\boldsymbol{s}_r^g}{y_{rk}^g} + \sum_{r=1}^{p_2} \frac{\boldsymbol{s}_r^b}{y_{rk}^b}\right)} \\
s.t. \quad & \boldsymbol{h}_l \geq \sum_{j=1,\neq k}^{n} \boldsymbol{\lambda}_j \boldsymbol{u}_j \\
& \sum_{j=1}^{n} \boldsymbol{\lambda}_j = 1 \\
& \boldsymbol{s}^-, \boldsymbol{s}^g, \boldsymbol{s}^b, \boldsymbol{\lambda} \geq 0
\end{aligned}
, \qquad (2)
$$

where $l = x, y, z$ and $\boldsymbol{u} = \boldsymbol{x}, \boldsymbol{y}, \boldsymbol{z}$, that is, $\boldsymbol{h}_x = \boldsymbol{x}_0$, $\boldsymbol{h}_y = \boldsymbol{y}_0$ and $\boldsymbol{h}_z = \boldsymbol{z}_0$. $\boldsymbol{s}^x$, $\boldsymbol{s}^y$, and $\boldsymbol{s}^z$ are the slacks of input and output vectors that should meet the constraint $\boldsymbol{s}^x, \boldsymbol{s}^y, \boldsymbol{s}^z \geq 0$. Then the SBM-efficient DMUs can be further identified and ranked by the efficiency index $\alpha^* \geq 1$.

[1] As Seiford and Zhu (1999), Zhu (2001), Chen (2005), and Lee et al. (2011) contend, infeasibility problems may occur when conducting analysis using the Super-efficiency model. However, in this study, no infeasibility is observed with the data.

2.2 Geographic detector model

To explore the driving forces of regional WUEs, the geographic detector model proposed by Wang et al. (2016) is frequently used (Cagliero et al., 2018; Chen et al., 2019b; Ding et al., 2018; Goudarzi et al., 2017; Hu et al., 2018; Jiang et al., 2018; Khan et al., 2019; Li et al., 2019; Onozuka and Hagihara, 2017). This model applies a *q*-statistic to detect the degree to which a factor u explains the spatial differentiation of attribute E in an observed region.

Suppose that the n DMUs in Section 2.1 can be divided into k layers, with each layer referring to a different region studied herein. Then, for layer $h(h=1,2,...,k)$, the variance σ_h^2 can be defined as $\sigma_h^2 = 1/N_h \sum_{i=1}^{n_h} \left(E_{hi} - \overline{E_h}\right)^2$, where E_{hi} represents the efficiency value of unit i in stratum h calculated by the model introduced in section 2.1. Variable $\overline{E_h}$ is the mean efficiency value of all DMUs in layer h. Similarly, the variance of all the samples can be calculated by $\sigma^2 = 1/N \sum_{i=1}^{n} \left(E_i - \overline{E}\right)^2$, where E_i is the efficiency value of DMU_i in all layers and $\overline{E}$ is the mean value of E_i. Combining the statistics' total sum of squares, $SST = N\sigma^2$, and within sum of squares, $SSW = N_h\sigma_h^2$, the *q*-statistic can be obtained: $q = 1 - SSW/SST$.

The value of q can be inferred between 0 and 1 from the formulas above, where 0 represents no stratified heterogeneity and 1 represents full stratification. The value of q indicates that $100 \times q\%$ of E can be explained by the explanatory variable u. The statistic value meets the "monotonous increase" property as the stratified heterogeneity increases. Therefore, the larger the value of q, the greater the stratified heterogeneity of E. If the stratification arises from the explanatory variable u, then a higher value of q implies stronger explanatory power of u on the attribute E, and *vice versa*. A q value of 1 indicates complete control of u on the spatial distribution of E, whereas 0 indicates no relationship between u and E.

2.3 Datasets and indicators

As part of the recent popularity of sustainability and quality of environmental development, water resources and WUE are also gaining more academic attention. Researchers use distinct variables to assess the performance and efficiency of water use (Azad et al., 2015; Geng et al., 2019; Li et al., 2018; Morales and Heaney, 2016; Wang et al., 2015; Watto and Mugera, 2019; Yao et al., 2018; Zhao et al., 2017; Zhou et al., 2018), based on which three input variables (asset, labor, and water consumption) and three output variables are selected, where the economic output (i.e., gross regional product [GRP] when gauging WUE at the overall level and added value at the industrial levels) is a desirable variable, and the emissions of AN and COD in wastewater (i.e., the main pollutants in wastewater) constitute the undesirable output variables.

Among the input indicators, the indicator asset indicates the total number of building and purchasing fixed assets in monetary form, which is named Total Investment in Fixed Assets (TIFA) (billion yuan) in the China Statistical

Yearbook. Labor refers to the total amount of employees hired. Here, we choose the Total Number of Employed Persons (TNEP) (million persons) as the representatives. The indicator water consumption is the key indicator for the WUE assessment, reflecting the amount of water used in the production process. In this paper, the Total Water Use (TWU) (billion tons) in the China Statistical Yearbook is chosen as a representative indicator. The gross national product (GRP) refers to the total value of all final products and services produced by all resident units in a region in a certain period of time, which is often regarded as an indicator to measure economic outputs. Given that efficient water use should include the economy performance, we select GRP (billion yuan) as the desirable output in this paper. When assessing industrial WUE, value-added of the three industries are chosen. In the China Statistical Yearbook, AN and COD in wastewater are regarded as the two most important pollutants in wastewater. Therefore, the total amount of emission of these two indicators, i.e., AN emission (ANE) and COD emission (CODE) were chosen as undesirable outputs.

For a more comprehensive and profound understanding of regional WUE in China, a multidimensional analytical framework is developed for the assessments (Fig. 1). The framework characterized in Fig. 1 has two *levels* (i.e., the overall level and industrial levels) and four *dimensions* for analysis of regional WUE. At the overall level, the measurement of regional WUE offers a global picture of China's regional WUE performance. Industrial WUE constitutes the second level of the analytical framework, which contains three dimensions. Here, China's regional WUE from the perspective of three industries, primary, secondary, and tertiary, are analyzed. Specific variables and data are chosen when evaluating WUE at different dimensions (Table 1).

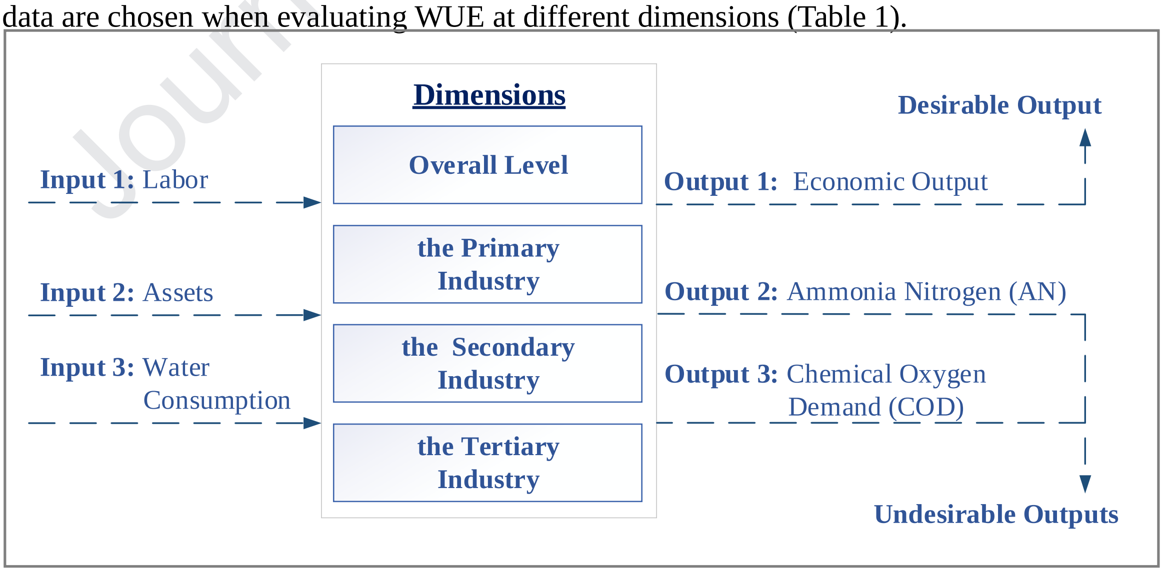


Fig. 1. Analytical framework for assessing regional WUE of China.

Table 1. Input and output variables for WUE assessments under different dimensions.

	Overall level	**the Primary industry (PI)**	**the Secondary industry (SI)**	**the Tertiary industry (TI)**
Inputs	(1) TIFA	(1) TIFA in PI	(1) TIFA in SI	(1) TIFA in TI

		(2) TNEP (3) TWU	(2) TNEP in PI (3) TWU in PI	(2) TNEP in SI (3) TWU in SI	(2) TNEP in TI (3) TWU in TI
Outputs	**Desirable**	(1) GRP	(1) Value-added of PI	(1) Value-added of SI	(1) Value-added of TI
	Undesirable	(1) ANE (2) CODE	(1) ANE of PI (2) CODE of PI	(1) ANE of SI (2) CODE of SI	(1) ANE of TI (2) CODE of TI

2.4 Descriptive statistics on indicators

The descriptive statistics are shown in Fig. 2a–2g. The assets input (average value) grew in all four dimensions. At the overall level, the average TIFA grew from ¥280.96 bn to ¥777.42 bn between 2005 and 2015, with an annual growth rate of 17.67%. The average TIFA of the secondary industry grew the fastest in the three industries. In 2005, the TIFA of the secondary industry was ¥123.88 bn, lower than that of the tertiary industry. After a ten-year growth period, the TIFA of the secondary industry was ¥724.13 bn, which was ¥300 bn higher than that of the tertiary industry in 2015 (Fig. 2a). In terms of the TNEP changes, three of the four dimensions increased over the years, whereas the TNEP of the primary industry experienced a decline (Fig. 2b). The changes of the third input variable—TWU—are relatively stable. The amount of water use grew from 18.17 bn tons in 2005 to a peak of 19.95 bn tons in 2013, and then reduced to 19.69 bn tons in 2015. Changes in the TWU of the other three industries were similar to that at the overall level (Fig. 2c).

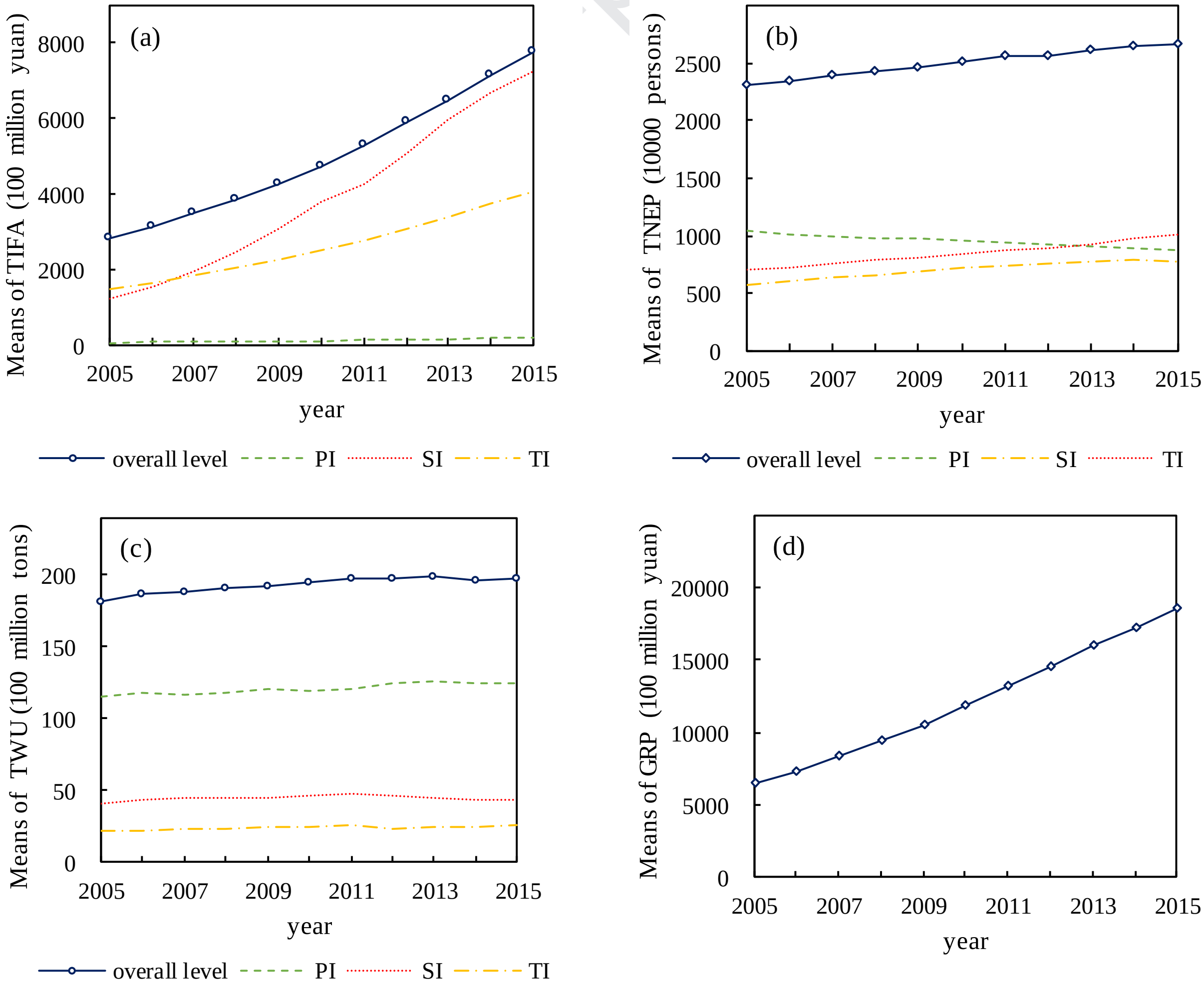
Desirable output variables increased at all the four dimensions after 2005 (Fig. 2d, 2e). At the overall level, the average GRP tripled from ¥642.67 bn to ¥1859.76 bn in 2005–2015. The average industrial added values of the primary, secondary, and tertiary industries increased simultaneously with an annual growth rate of 5.41%, 22.05%, and 19.41%, respectively. It can be found from Fig. 2e that the primary industry had both the lowest value and annual growth rate among the three industries.

When analyzing changes in undesirable outputs, period 2005–2015 was divided into two phases (period 2005–2010 and 2011–2015) due to the revision of statistical scope[1]. Fig. 2f illustrates the changing process of ANE in wastewater[2]. ANE in the three dimensions (i.e., the overall level, the secondary industrial level, the tertiary industrial level) all experienced continuous decreases from 2005 to 2010. Although the total amount of ANE in the secondary industry was less than that in the tertiary industry, it changed with a higher reducing rate faster than in the tertiary industry, indicating a higher capability of cleaner production in the secondary industry. The total amount of ANE at the overall level also decreased, effected more by the changes of ANE

[1] In 2011, statistical scope in wastewater was expanded to 5 parts by the Ministry of Environmental Protection, PRC: industry source, agricultural source, urban living source, automotive vehicle, centralized pollution abatement. Indicators of statistical system, method of survey, and related technologies were also revised, rendering incomparability between undesirable outputs in 2010 and 2011. Data-smoothing was not adopted here for the purpose of observing actual changes. Therefore, period 2005-2015 was divided.

[2] Data on ANE of the primary industry from 2005 to 2010 were not given. Therefore, in the first period, changes at the primary industrial level were not analyzed. The same is true of data on CODE.

in the secondary industry. Performance of the tertiary industry in the second period (2011–2015) was better than the previous period, during which the ANE declined from 47600 tons in 2011 to 43300 tons in 2015 with an average annual decrease of 1075 tons. However, the total amount of ANE in the tertiary industry was the highest among the three industries, with ANE in the primary industry performing second and the secondary industry performing the best. The same is true for CODE from 2005 to 2010 (Fig. 2g), the total amount of which reduced from 456.2 thousand tons to 349.4 thousand tons. Means of CODE in the secondary industry decreased from 179.0 thousand tons in 2005 to 140.3 thousand tons in 2010 with an average annual decrease rate of 4.70%, which is 3.59 times that of the tertiary industry (1.31%) over the same period. In the second period (2011–2015), the annual decline rate of the secondary industry is still the highest among the three industries, reaching 4.63%. The rate of the tertiary industry also improved to 2.54%, which was close to the overall level (2.89%). The same situation occurs in the primary industry, CODE in which falling from 382.6 thousand tons in 2011 to 344.7 thousand tons in 2015, reaching an average reduction rate of 2.57% annually.



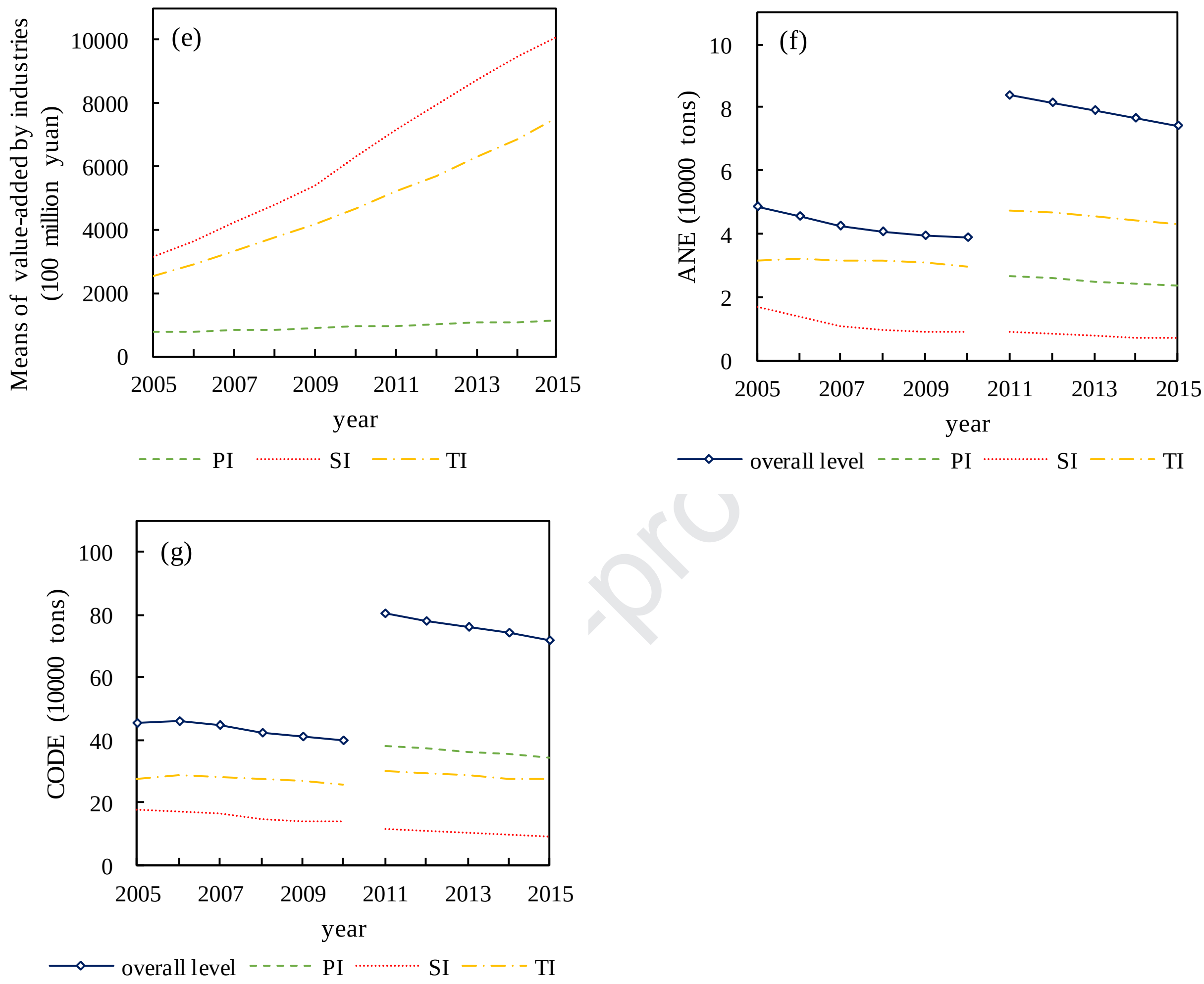


Fig. 2. Changes in means of TIFA (a), TNEP (b), TWU (c), GRP (d), value-added of the three industries (e), ANE (f) and CODE (g) in wastewater from 2005 to 2015.

3. Results

The overall and industrial WUE of the DMUs can be calculated based on the model developed in Section 2. Results show an average WUE lower than 1 at overall level (Fig. 3a), indicating that China's current WUE should be enhanced. The industrial WUE indices are also relatively low (Fig. 3b), among which the WUE index of the primary industry is the highest, with an average value of 0.8946. (The WUE index of the primary industry can only be calculated from 2011 to 2015 because of lack of statistics for the undesirable outputs.) This may correspond with accumulated experience, such as water-saving irrigation in the long history of agricultural production in China. In general, WUE of the secondary industry ranks second with an average value of 0.5772, higher than that of the tertiary industry at an average of 0.5484. After industrial restructuring and upgrade, the WUE index of the secondary industry slumped in 2015. This value has been at its lowest level since 2005, placing it at the bottom and allowing the tertiary industry to surpass it after 2011.

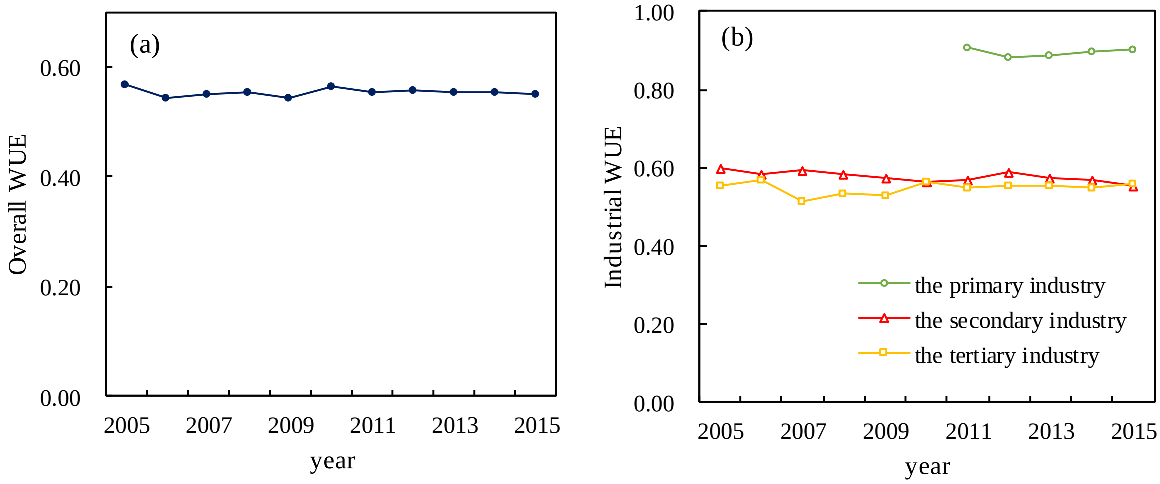


Fig. 3. Average WUE at the overall level (a) and industrial levels (b) in China from 2005 to 2015.

The average WUE index value of each province from 2005 to 2015 is calculated based on the WUE distribution map in Fig. 4. The efficiency of water use in the eastern region, especially along the eastern and southern coasts, is significantly higher than that in the central and western regions. By contrast, WUE in northwest China lags. Although WUE in central and western China is relatively low, some provinces, such as Qinghai and Sichuan Province, have higher WUE scores than the surrounding provinces. They form small peaks in the WUE index for the central and western regions, whereas the surrounding low-WUE provinces such as Anhui and Jiangxi Province are collapsed in the figure.

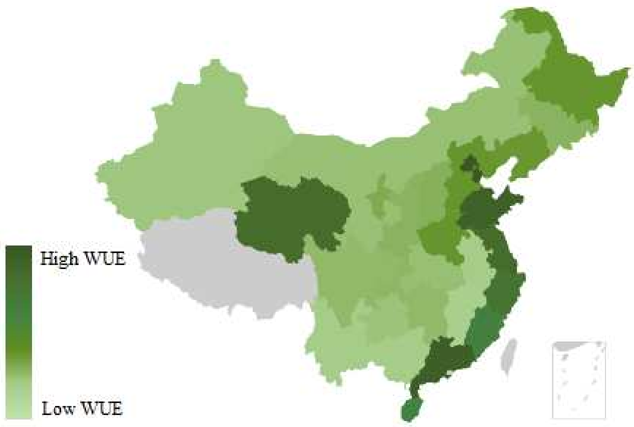


Fig. 4. Distribution of the average WUE index value of 30 provinces from 2005 to 2015.

3.1 Regional heterogeneity of water-use efficiency in China

For a more comprehensive analysis of regional WUE in China, WUE index values of regions with different water distribution characteristics are investigated herein. Numerous water resources indicators and indices were used to measure the degree of water scarcity, including Water System Vulnerability (Gleick, 1990), Water Availability Index (Meigh et al., 1999), Water Resources Vulnerability Index (Shiklomanov, 1990; Vorosmarty et al., 2000), and Water Poverty Index (Sullivan, 2002; Sullivan et al., 2003). Particularly, the Falkenmark Water Stress Indicator (Falkenmark et al., 1989) is globally accepted to evaluate regional water resources availability and scarcity. It sets the threshold of annual renewable surface water and groundwater availability of 1700 m^3 per capita. Based on this threshold, several levels of water scarcity (e.g., water stress, chronic water scarcity, and beyond the water barrier) are graded. Combined with the water shortage classification provided by World Water Assessment Programme (2015), 30 provinces herein are grouped into five categories according to the average annual water resources availability per capita (Table 2). These categories include *water abundance*, *water vulnerability*, *water stress*, *water scarcity*, and *water absolute scarcity*. The data on water resources per capita are taken from China's Statistical Yearbook (2006–2016). The amount of water resources per capita is calculated based on the urban population, which changes with respect to the sum of the urban census register population and transient population.

Fig. 5 illustrates the distribution of the water scarcity conditions of different provinces. It can be found that, except for Shaanxi and Shanghai, the provinces of absolute scarcity are mainly located in north China, most of which are adjacent to each other. Water scarcity provinces are scattered but are invariably found in north China. Except for Jilin Province, water stress provinces closely surround the absolute scarcity area. Water vulnerability provinces are distributed in northeast and southeast China, while water abundance provinces are located in western and southern China. Fig. 5 also reveals an interesting feature of the water scarcity distribution pattern in mainland China: Link the northwest end to the southeast and a boundary appears. Along this boundary, the southwest region is abundant in water resources, whereas the northeast region is relatively deficient.

Table 2. Five water resources distribution regions and constituent provinces.

Water resources status	Water resources per capita (cu. M/person)	Constituent provinces	Number of provinces
Water abundance	2500≤x	Fujian, Jiangxi, Hunan, Guangxi, Hainan, Sichuan, Guizhou, Yunnan, Qinghai, Xinjiang	10
Water vulnerability	1700≤x<2500	Inner Mongolia, Heilongjiang, Zhejiang, Guangdong, Chongqing	5
Water stress	1000≤x<1700	Jilin, Anhui, Hubei, Shaanxi	4
Water scarcity	500≤x<1000	Liaoning, Jiangsu, Gansu	3
Water absolute scarcity	0<x<500	Beijing, Tianjin, Hebei, Shanxi, Shanghai, Shandong, Henan, Ningxia	8

Fig. 5. Five water resources distribution regions in this study.

Fig. 6 illustrates the overall and industrial WUE index values of the five regions. Despite having the scarcest water resources, the absolute scarcity region has the highest WUE index values. However, the stress region performs the worst; it has the lowest WUE in all dimensions. The abundance region is also inefficient in water use, ranking third at the primary industrial level and second in the secondary and tertiary industrial levels. On the whole, the WUE index value of the five regions is the highest in the first production and is ahead of the WUE for the other three aspects.

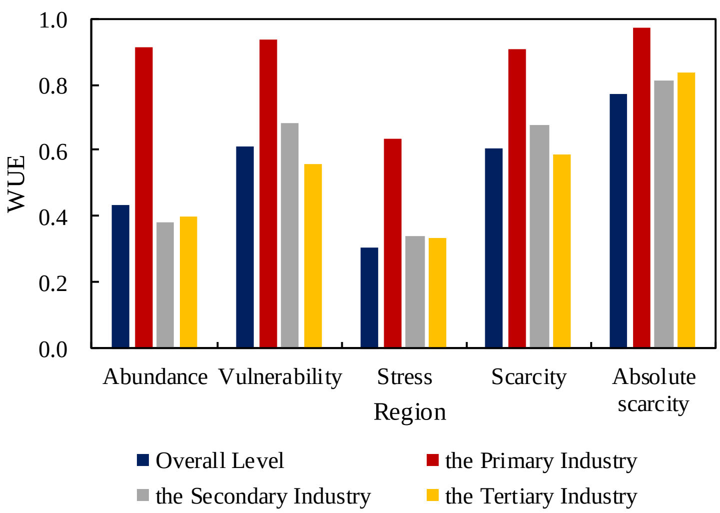


Fig. 6. WUE index values of different regions under all measured dimensions.

At the overall level, the WUE index values of the absolute scarcity and vulnerability regions are always above the national average (Fig. 7a). However, differences exist between the two regions with high overall WUE. From 2005 to 2015, the WUE index value of the absolute scarcity region increased above the national average and compared with other regions at a stable rate. On the contrary, the vulnerability region failed to maintain its advantages. Though it held a leading position against four regions (except the absolute scarcity region), it continued to decline and almost matched the scarcity region by 2010.

However, the scarcity region has been improving since 2007 and now exceeds the national average despite its initial low status.

In general, all the five regions show a well-performing WUE index at the primary industrial level. Four of the five regions (i.e., water abundance, vulnerability, scarcity, and absolute scarcity) have an index value higher than the national average for every year between 2011 and 2015 (Fig. 7b). Regarding the overall WUE, there exists an efficiency of water use even in the absolute scarcity region. Notably, the WUE of the primary industry exhibits characteristics of annual changes, where the efficiency gap among regions is larger in odd years than that in even years.

Regarding the WUE index value of the secondary industry, the water absolute scarcity region ranks first, whereas the stress and abundance regions fall at the bottom (Fig. 7c). Significant changes occur in the vulnerability and scarcity regions. At the beginning, the WUE index value in the vulnerability region is as almost high as that of the absolute scarcity regions. From 2010 onward, it descended rapidly and was surpassed by the WUE index value of the scarcity region, which, at the same time, was steadily increasing. However, the scarcity region failed to maintain this improvement in the secondary industrial WUE. A deterioration with the vulnerability region in and after 2013 can be observed. Meanwhile, the improvement of the secondary industrial WUE in the stress and abundance regions accelerated. The efficiency gap between the five regions subsequently narrows.

Compared with the efficiency of the primary and secondary industry, the efficiency of the tertiary industry shows evident differences among the echelons, which are categorized by the regional WUE performance. The first echelon has only one region, the absolute scarcity region. This region’s WUE is not only the highest between the five regions, but also much higher than the national average WUE. The second echelon includes the vulnerability and scarcity regions. At the very beginning, especially in the year 2008 and before, it is challenging to count the scarcity region as a member of the second echelon. Nevertheless, in 2009, its WUE improved significantly and the index value surpassed that of the vulnerability region. The third echelon includes the abundance and stress regions, whose WUE index values have been relatively poor and almost unchanged (Fig. 7d).

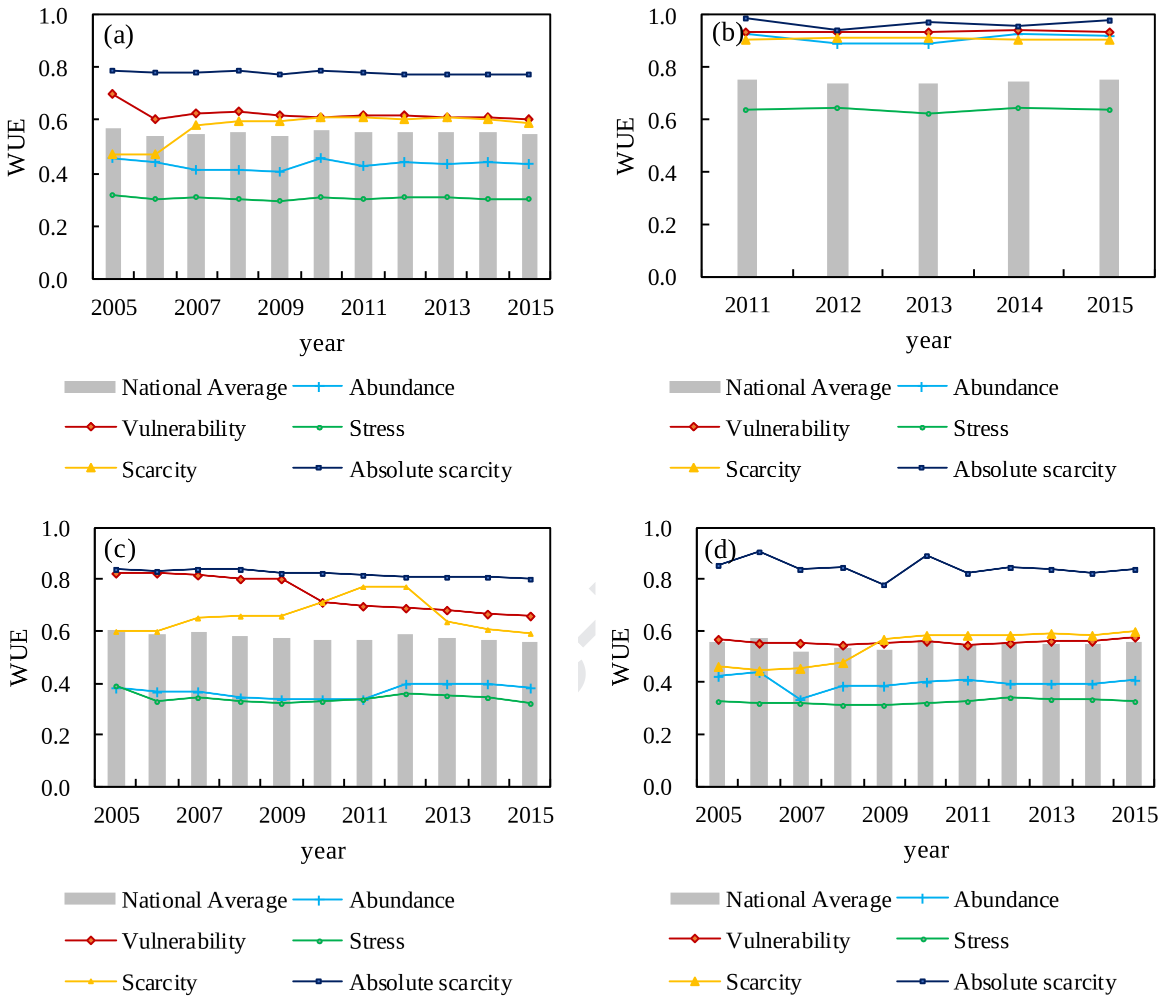


Fig. 7. WUE index values at the overall level (a), the primary industrial level (b), the secondary industrial level (c) and the tertiary industrial level (d) from 2005 to 2015.

3.2 Driving forces of regional water-use efficiency differences

Driving forces on the regional WUE are examined based on industrial structure (IS), population structure (PS), scientific and technological levels, and educational level. The evolution of the secondary industrial WUE is similar to that of the overall WUE regarding industrial structure. Hence, the proportion of the secondary industry in the three industries is selected as the representative indicator of industrial structure. The urbanization rate indicator is chosen to stand for population structure. Further, scientific and technological development can affect the production process and will inevitably affect the efficiency of water resources use. Input and output indicators are the two aspects that are frequently used to assess the development status of science and technology. Therefore, the R&D input intensity (RDII) is taken as input, whereas the proportion of R&D personnel (RDP) and the added value of the high-tech production (HTP) is our output. Educational factors are also considered when identifying the driving forces. Similar to the field of science and technology, educational funds (EF) are taken to represent the input of education. Given that the number of university students may not reflect the educational quality due to delayed graduation or even dropping out, the number of higher education graduates (HEG) is chosen to represent the education output. Because only few provinces exist in stress and scarcity regions and both regions have similar water resources endowment properties, the stress and scarcity regions are combined into one region in this analysis.

The effect of the indicators above on WUE index value in the four regions is reported in Table 3. Results illustrate that WUE index values in different regions are driven by different forces. RDII is the only dominant force in WUE in the absolute scarcity region, while the stress and scarcity region's WUE index values are also dominated by RDP and RDII. The driving forces in the vulnerability region are PS and EF; both affect the WUE index value remarkably in this region. In contrast, the WUE index value in the abundance region is more affected by RDII.

Table 3. *Q*-statistic of the driving forces on the WUE index value in four regions.

	IS	PS	RDII	EF	HTP	RDP	HEG
Absolute scarcity	0.2117	0.3185	<u>0.4926</u>	0.3059	0.2177	0.3803	0.2138
Stress and Scarcity	0.0525	0.2993	<u>0.4804</u>	0.2110	0.1076	<u>0.4828</u>	0.1115
Vulnerability	0.0939	<u>0.4926</u>	0.2426	<u>0.4872</u>	0.0658	0.3443	0.2036
Abundance	0.2106	0.2196	<u>0.3315</u>	0.1303	0.1920	0.1134	0.2072

A common phenomenon can be observed in the results: effects of science and technology-related indicators are more significant on regional WUE. Although factor PS has not become the dominant driving force in most regions (except the vulnerability region), it has a remarkable effect on the WUE index value of the other three regions at an explanation level of 31.85%, 29.93%, and 21.96%, respectively. Thus, its influence degree is higher compared with the other three aspects in most cases. Factor IS affects the absolute scarcity and abundance regions more than the other two regions. Among the four detected regions, the driving forces had a balanced effect on the absolute scarcity and abundance regions, whereas WUE in the stress and scarcity regions was driven less by the population-related indicator. This result is similar to the WUE index value in the vulnerability region.

Notably, the effect of the indicators on the regional WUE index value is not mutually independent. Thus, the interaction among indicators may exert a higher degree of influence on the regional WUE index value. The interaction detection module of the Geodetector software can identify the driving effect of the interaction between two drivers on WUE in different regions to a higher degree. Based on the results of this module, the enhancement effect of the interaction among driving forces on the WUE index value includes bi-enhancement and nonlinear-enhancement. Enhancement means that the synergistic effect of the impact forces exceeds the individual or cumulative effect of the two forces. In the case of bi-factors enhancement, the effect of interaction between factor x and factor y is higher than the maximum effect of each factor. In the case of nonlinear enhancement, the effect of the interaction between the two factors is higher than the sum of their individual effects.

Assume that factor x and factor y are two driving factors of regional WUE, so $x \bigcap y$ is the interaction of x and y. Then values of effect can be represented by $E(x)$, $E(y)$ and $E\left(x \bigcap y\right)$. Further, bi-factors enhancement can be formulated as: $E\left(x \bigcap y\right) > \max\left(E(x), E(y)\right)$, and nonlinear enhancement can be formulated as: $E\left(x \bigcap y\right) > E(x) + E(y)$. Table 4 reports the combinations of the top four indicators with the largest WUE index value interaction for each region.

Table 4 reports the interactions among the indicators that are dominant of WUE in different regions. It can be found that the indicators IS, RDII, and HEG are the essential indicators of dominant interactions of WUE in different regions. Their mutual interactions and interactions with other indicators are highly influential. For example, RDII∩HEG and IS∩PS are dominant in the absolute scarcity region. IS∩HTP and RDII∩HEG are dominant in the stress and scarcity regions. WUE in the vulnerability region is mainly affected by the interactions of IS∩EF, RDII∩HEG, as well as IS∩HTP. WUE in the abundance region is affected by the interactions between IS∩RDII and RDII∩HEG.

An important common feature is also noticed: The interaction between RDII and HEG has a significant impact on WUE in all four regions (absolute scarcity, 49.80%; stress and scarcities, 49.35%; vulnerability, 49.38%; and abundance, 49.61%), reflecting the strong incentive effect of technology and education on the improvement of regional WUE. The interactions among the driving forces that influence regional WUE exhibit an obvious convergence of water resource endowment characteristics.

Table 4. Dominant interactions on the WUE index value in different regions.

	Absolute scarcity	**Stress and Scarcity**	**Vulnerability**	**Abundance**
Dominant interaction 1	RDII ∩ HEG 0.4980$^{\triangle}$	PS ∩ HTP 0.5000$^{\triangle}$	IS ∩ HTP 0.5000$^{\blacktriangle}$	RDII ∩ HEG 0.4961$^{\triangle}$
Single effect	RDII 0.4926 HEG 0.2138	PS 0.2993 HTP 0.1076	IS 0.0939 HTP 0.0658	RDII 0.3315 HEG 0.2072
Dominant interaction 2	RDII ∩ HTP 0.4954$^{\triangle}$	RDII ∩ HEG 0.4935$^{\triangle}$	RDII ∩ HEG 0.4938$^{\blacktriangle}$	IS ∩ RDII 0.4957$^{\triangle}$
Single effect	RDII 0.4926 HTP 0.2177	RDII 0.4804 HEG 0.1115	RDII 0.2426 HEG 0.1115	IS 0.2106 RDII 0.3315
Dominant interaction 3	HTP ∩ HEG 0.4061$^{\triangle}$	IS ∩ HTP 0.4920$^{\triangle}$	RDII ∩ RDP 0.4930$^{\triangle}$	RDII ∩ EF 0.4334$^{\triangle}$
Single effect	HTP 0.2177 HEG 0.2138	IS 0.0525 HTP 0.1076	RDII 0.2426 RDP 0.3443	RDII 0.3315 EF 0.1303
Dominant interaction 4	IS ∩PS 0.3797$^{\triangle}$	RDP ∩ HEG 0.4898$^{\triangle}$	IS ∩ EF 0.3188$^{\triangle}$	EF ∩ HEG 0.3589$^{\triangle}$
Single effect	IS 0.2117 PS 0.3185	RDP 0.4828 HEG 0.1115	IS 0.0939 EF 0.4872	EF 0.1303 HEG 0.2072

Note: Notation$^{\triangle}$ represents bi-factors enhancement of interaction. Notation $^{\blacktriangle}$ represents nonlinear enhancement of interaction.

4. Conclusions

In this study, WUE and its evolutionary process in 30 provinces in mainland China from 2005 to 2015 are evaluated by the Super-USBM model under a multidimensional analytical framework. Three input indicators, one desirable output indicator and two undesirable output indicators were selected for the assessment. Driving forces of the regional WUE are also identified.

The main findings are as follows: (1) At the national average level, the overall and industrial WUE index values are less than 1, indicating that the current WUE in China needs improvements. The primary industry has the highest efficiency, followed by the secondary and tertiary industries, in that order. The tertiary industry surpasses the secondary industry owing to the former's industrial restructuring, upgrade, development, and maturity. (2) At the regional level, water abundance, vulnerability, stress, scarcity, and absolute scarcity, grouped according to the water resources availability per capita, are all efficient in terms of water use in the primary industry. Secondary industrial water-use performance in the regions of water vulnerability, stress, and scarcity is better than that of the tertiary industry in the regions of water abundance and absolute scarcity. Although short of water resources in per capita terms, the water absolute scarcity region, located in north China surrounding the Bohai sea, has developed with the highest WUE index value in the four dimensions. (3) At the provincial level, provinces in the eastern coastal region, especially the south-eastern coastal region, have the highest WUE, whereas those in the interior south-eastern and south-western region have the lowest in relation. The WUE index values for Beijing and Shanghai rank in the top five at all four dimensions. Tianjin and Guangdong follow, with WUE index values leading at the overall, secondary industrial, and tertiary industrial levels. (4) Industrial structure, R&D intensity, and higher education are the main driving forces of WUE. Their mutual interactions and interactions with other indicators are highly influential. Among the driving forces, indicators for the urbanization rate and education expenditure are the main forces causing the regional differences in water-use performance.

Policy implications for improving WUE arise from the findings of this research. First, given the imbalanced and uncoordinated development of WUE in China, it is important to implement a strategy of coordinated regional WUE development. Second, WUE can be improved by exploiting the radiation effect wherein advantages of high-efficiency areas spread to low-efficiency areas. For example, the absolute scarcity region is surrounded by the stress region. The former has the highest WUE, whereas the latter has the lowest, forming a sharp contrast. This phenomenon can be used as heuristic information to drive the development of the stress region and improve China's overall WUE efficiency by stimulating the absolute scarcity region. Third, the results of driving forces identification indicate that incentive policies should be designed to increase investments in science and technology, improve the quality of education, and optimize the industrial structure to, in turn, positively affect WUE.

Future research should include models that can avoid the infeasibility problem for the fully ranked analysis of regional and industrial WUE in China. Inter-industry heterogeneity may be further considered during the inter-industry analysis. Also, assessment can be applied at a more microscopic level, such as the municipal level, to offer a more accurate and precise picture of the regional water use performance in

China.

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- A multidimensional analytical framework is developed for inter-industrial analysis.
- Super-SBM model is applied for full ranking of decision making units.
- Both economic and environmental efficiency of water-use are considered.
- Driving forces of regional heterogeneity of efficiency are identified.

Declaration of interests

☒ The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

☐The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: