Sustainability in Environment
ISSN 2470-637X (Print) ISSN 2470-6388 (Online)
Vol. 4, No. 4, 2019
www.scholink.org/ojs/index.php/se

Original Paper

Water Resource Utilization Efficiency (WRUE) for Prefecture-Level Cities of Jiangxi, China: A Three-Stage DEA and Bootstrap DEA Approach

Mianhao Hu[1*], Yunlin Hu[1] & Juhong Yuan[2]

[1] Institute of Ecological Civilization, Jiangxi University of Finance & Economics, Nanchang, China

[2] Institute of Environment and Plant Science, Jiangxi University of Finance and Economics, Nanchang, China

[*] Mianhao Hu, Institute of Ecological Civilization, Jiangxi University of Finance & Economics, Nanchang, China

Received: October 12, 2019 Accepted: October 26, 2019 Online Published: October 30, 2019

doi:10.22158/se.v4n4p255 URL: http://dx.doi.org/10.22158/se.v4n4p255

Abstract

In the present study, For China's prefecture-level cities of Jiangxi, their respective Water Resource Utilization Efficiency (WRUE) from 2006 to 2015 was evaluated in this study, by applying a three-stage DEA and bootstrap DEA model. The results revealed that a comprehensive efficiency of water resources utilization in prefecture-level cities of Jiangxi remained at a relatively low level. The scale of investment in these prefecture-level cities is a key factor restricting their WRUE. However, we found that external environmental variables greatly influenced this efficiency. The spatial changes of DEA effective cities presented the evolution character of change from clear contiguous to complicated scattered. Moreover, our results suggest the bootstrap method can provide more accurate results for WRUE than those from a three-stage DEA. Finally, based on these results, corresponding policy recommendations are put forward in this study.

Keywords

water resource utilization efficiency, *three-stage DEA*, *bootstrap-DEA*, *comprehensive efficiency*

1. Introduction

Water is an irreplaceable basic natural resource and a strategic economic one for maintaining human civilization and social progress. However, because of long-term overconsumption to fuel rapid economic development, water resources have now *become* the main factor *limiting* regional economic sustainable development in China (Zhou et al., 2017). *Jiangxi Province,* located in *the middle and lower southern reaches* of *the Yangtze River*, is rich in water resources but their development and utilization is relatively low: this *province*'*s use*s just 16.8% of it total water resources, much lower than China's provincial average of 22% (Xie & Zhou, 2014). In addition, the uneven distribution of water resources further limits the availability of water for human economic use. With its recent rapid economic growth, increasing urbanization, and growing population, Jiangxi's water resources now face severe problems, namely in the form of *severe water pollution,* f*lood disaster,* and an ecologically deteriorated aquatic environment. Indeed, water resources are recognized as the key factor constraining *social and economic development* and urbanization in Jiangxi (Hu et al., 2018). This precarious situation has captured the attention of both the central and local governments. In 2012, the ''Opinions of the State Council on Applying the Strictest Water Resources Control System'', published by the Chinese Central Committee of the Communist Party and the State Council, drew a red line for water efficiency achieved by 2030 (MWR, 2012). In this context, the *rational development and* efficient utilization *of water resources* is prominently recognized as an urgent task underpinning regional *sustainable development* (Wang et al., 2015).

In recent years, different types of Data Envelopment Analysis (DEA) models have been used by *researchers* to evaluate *Water Resources Utilization Efficiency (*WRUE). For example, André et al. (2010) used a modified DEA model to estimate the agricultural water efficiency in Spain, and later Sun and Zhao (2013) applied the undesirable output radial direction DEA model to 31 provinces in China to measure their level of water resource utilization relative to environmental technology. Marques et al. (2014) relied on DEA to study institutional and environmental factors affecting the efficiency of Japanese water utilities, while Wang, and Lu (2014) used an input-oriented DEA model to analyze agricultural water use efficiency and its regional differences. More generally, in a recent review paper, Worthington (2014) shows how to assess urban water supply and production efficiency by using DEA and Stochastic Frontier Analysi (SFA) models. Concerning DEA's application in China, researchers have measured WRUEs of 31 provinces with a DEA-SBM model that considered an undesired output (Sun et al., 2014), measured WRUE at the inter-provincial level with a DEA output *directional distance function* (Ma et al., 2016), proposed a two-stage evaluation method based on DEA model to analyze industrial water system efficiency in 30 provincial regions (Wang et al., 2016), and have analyzed the water efficiency of cities in Gansu Province with the two-stage DEA model to (Ren et al., 2017).

This research on WRUE from different perspectives is robust and insightful, being critical for informing the current study. Specifically, on one hand, since *they focus on China as whole or its* economically developed *provinces with* serious water resource problems, few studies exist of *economically underdeveloped* prefecture-level cities with abundant water resources using statistical methods, largely because data is lacking. On the other hand, *it has been argued that* efficiency studies using a DEA model eliminating the influence of environmental variables and random error could result in biased estimates (Carvalho & Marques, 2016), with DEA efficiency scores influence by samples differing in size leading to biased results (Zhang & Bartels, 1998). Additionally, the *DEA's* relative *efficiency value* does not denote absolute efficiency, and literature on this lacks empirical measurements of WRUE. However, the bootstrap DEA method permits the sensitivity of efficiency scores relative to the sampling variation of the frontier to be analyzed, thus precluding problems of asymptotic sampling distributions (Simar & Wilson, 1998, 2000a, 2000b).

Here, using Jiangxi's 2006-2015 data, we hypothesized a more accurate measurement of WRUE for its prefecture-level cities by using the three-stage DEA and bootstrap DEA models. The three-stage DEA can examine the impact on the traditional DEA efficiency scores from environmental variables by filtering out the latter's effects, to which the bootstrap DEA is applied to reduce the deviation in differences between the resulting and original values. In so doing, this study not only is of strong practical significance to water conservation in Jiangxi, but it also provides key recommendations for government decision-makers to better plan for the efficient use of water resources among prefecture-level cities.

2. Methods

2.1 Stage I: Traditional DEA Model

The traditional DEA method, first described by Charnes et al. (1981), measures a producer's performance in terms of complex factors of inputs and outputs. The BCC (Banker, Charnes, & Cooper, n.d.) model of DEAP2.1 (Variable Returns to Scale, VRS) was used to calculate WRUE in our paper. When set to evaluate the k production unit efficiency, assuming that for l kinds of input index and m kinds of output indicators the set x_{jl} represents the l kind of resource inputs in the j^{th} unit and y_{jm} represents the m kind of output in j^{th} unit, the DEA model for unit k can be written as follows (Fried et al., 2002; Zhao et al., 2018):

$$Min\left[\theta - \varepsilon\left(e^T s^- + e^T s^+\right)\right] \tag{1}$$

$$s.t\begin{cases}\sum_{j=1}^{k} x_{ji}\lambda_j + s^- = \theta x_1^n \\ \sum_{j=1}^{k} y_{jm}\lambda_j - s^+ = y_m^n \\ \lambda_j \geq 0,\ \ k = 1, 2, \cdots, n;\quad s^- \geq 0,\ s^+ \geq 0\end{cases}$$

The efficiency value calculated formula (1) is the termed the Comprehensive Efficiency (CE), which can be decomposed into Pure Technical Efficiency (PTE) and Scale Efficiency (SE). That is, CE = PTE × SE. Hence, CE is a comprehensive measurement and evaluation of the resource allocation ability and the resource efficiency in the case of Variable Returns to Scale (VRS). The θ_b is a PTE index, with $0 < \theta_b \leq 1$, $\theta \geq 0$, and SE = θ/θ_b with $0 <$ SE ≤ 1; when $\theta_b = 1$ or SE =1, PET or SE is optimal, respectively.

2.2 Stage II: SFA Regression Model

Input/output slack variables are *influenced* by three factors: environmental variables, random effects, and management efficiency (Fried et al., 2002). Thus, the objective of the Stage 2 analysis is to decompose Stage 1 slacks into the above three influences. The Stochastic Frontier Analysis (SFA) can do this, in which Stage 1 slacks are regressed against a set of environmental variables, which both captures and distinguishes the effects of managerial inefficiency and statistical noise. The regression equation of the SFA model has the following form (Zeng et al., 2016):

$$S_{ni} = f^n\left(z_i;\beta^n\right) + v_{ni} + u_{ni};\quad n = 1, 2, \cdots, N,\quad i = 1, 2, \cdots, \tag{2}$$

where S_{ni} is the slack variable of the I^{th} sample investment in the n^{th} DMUs (decision making units); $z_i = (z_{1i}, z_{2i}, \ldots, z_{ki})$ are the k observable environmental variables; β^n is the parameter to be estimated for the environmental variables; the term $f^n(zi; \beta^n)$ represents the effect of the environmental variables on the redundant variables S_{ni}; the term $v_{ni} + u_{ni}$ is the composed error structure, for which $v_{ni} \sim N\left(0, \sigma_{vn}^2\right)$ represents the random variable effect and $u_{ni} \geq 0$ represents management inefficiency. Producers' adjusted inputs are constructed from the results of the Stage 2 SFA regressions, by using the following equation:

$$\begin{aligned} x_{ni}^A &= x_{ni} + \left[\max_i\left\{f\left(z_i;\hat{\beta}^n\right)\right\} - f\left(z_i;\hat{\beta}^n\right)\right] + \left[\max_i\left\{\hat{v}_{ni}\right\} - \hat{v}_{ni}\right] \\ n &= 1, 2, \cdots, N,\quad i = 1, 2, \cdots, I \end{aligned} \tag{3}$$

Where x_{ni} and x_{ni}^A are the level of input quantities in each DMU before and after the adjustment, respectively. The first bracket states that all DMUs are adjusted to the same external environment. The second bracket adjusts the random errors of all DMUs into the same context so that each DMU encounters the same operating environment and has the same luck.

To obtain estimates of v_{ni} for each producer, the statistical noise is separated from managerial inefficiency in the residuals of SFA regression models (2). The composed error terms in equation (2) are then decomposed by using the methodology of Jondrow et al. (1982) and Fried et al. (2002), with the following equation:

$$\begin{aligned} &\hat{E}\left[v_{ni}\,|v_{ni} + u_{ni}\right] = s_{ni} - f\left(z_i;\hat{\beta}^n\right) - \hat{E}\left[u_{ni}\,|v_{ni} + u_{ni}\right] \\ &n = 1, 2, \cdots, N,\quad i = 1, 2, \cdots, I \end{aligned} \tag{4}$$

2.3 Stage III: Adjusted DEA Model

The original input data x_{ni} is replaced by x_{ni}^A, which is the adjusted input data. The BCC is then used to analyze efficiency. The efficiency of each DMU is obtained by eliminating the effects of environmental variables and statistical noise, to better convey the actual operation status of each DMU. Hence, the output of stage 3 is a DEA-based evaluation of producer performance denoted solely in terms of managerial efficiency, having first eliminated the effects of the operating environment and statistical noise.

2.4 Bootstrap DEA Model

DEA estimators were shown as biased by their construction, according to Simar and Wilson (1998, 2000b, 2008). Combining the DEA model with bootstrap techniques is therefore needed to correct and estimate the bias of the DEA efficiency indicators. In this study, the bootstrap-DEA method, of *sampling with replacement*, with B = 2000 bootstrap replications and confidence intervals of 95%, was applied to bias-corrected estimates of CE from stage III, so as to provide a robust estimate of true CE in the prefecture-level cities of Jiangxi. The following steps were taken for this bootstrap DEA estimation (Simar & Wilson, 1998, 1999, 2000b):

(1) Use the decision making unit (DMU) efficiency score $\hat{\theta}_i$, where i =1, 2, ..., N, obtained from the stage 3-DEA estimation approach.

(2) Obtain $\hat{\beta}_i^*$ via repeatedly sampling through ($\hat{\theta}_1$, $\hat{\theta}_2$,... $\hat{\theta}_n$).

(3) Use the formula $x_i^* = \hat{\theta}_i\, x_i \big/ \hat{\beta}_i^*$ to adjust the input value of x_i.

(4) Apply the DEA model to the adjusted input and original output to obtain the efficiency score $\hat{\theta}_i^*$, where i =1, 2, ..., N.

(5) Repeat the above steps B times, then calculate the deviation in the efficiency score ($\hat{\theta}_i$) to obtain the corrected efficiency score (θ_i').

$$\begin{cases} \hat{bias}_i = \dfrac{1}{B}\sum_{b=1}^{B}\hat{\theta}_{ib}^* - \hat{\theta}_i \\ \theta_i' = \hat{\theta}_i - \hat{bias}_i \end{cases} \qquad i = 1, 2, \ldots, N \tag{5}$$

3. Variable Selection and Data Sources

3.1 Selection Input and Output Variables

Labor, capital, and natural resources are the most important components of production in human activities, which if effectively combined can generate economic output. Thus, after considering the selection of water resources evaluation indicators in the extant literature (Dou, 2014), as well as the integrity and availability of data, *we used total water, fixed assets investment,* and *labor force as the input variables in this study. The* output variables used were Gross Domestic Product (GDP) per city and Chemical Oxygen Demand (COD) *discharge*; real GDP per year was calculated *relative to* 2006, and COD consisted mainly of *industrial wastewater* and *domestic sewage discharges*.

3.2 Selection of Environmental Variables

Environmental factors are also known as external factors (or externalities), that is those that can affect water resource efficiency but are not subjective or controllable. In this study, environmental factors are divided into three kinds: natural, economic, and social In this study, p*er capita water resources* was designated the natural variable, *per capita GDP* the economic variable, while *industrial structure* (*ratio of primary industry GDP to* total *GDP [i.e., PIGDP/TGDP]*) and *population density* were the social variables.

All the above data were derived from the *Jiangxi Provincial Statistical Yearbook (*2006-2015) and the *Jiangxi* Province *Water Resources Bulletin* (2006-2015).

4. Results

4.1 Measurement of WRUE Using a Three-Stage DEA Model

4.1.1 Stage I: Empirical Results Using the Traditional DEA

The resulting efficiency and returns to scale for prefecture-level cities of Jiangxi are shown in Figure 1 and Table 1. From the first stage of the traditional DEA efficiency measurement, evidently the CE was 0.914 and the PTE and SE were 0.937 and 0.975, respectively, on average. Therefore, there is still room to improve the CE of water resource utilization in Jiangxi. Since the SE was higher than the PTE, this implies low efficiency as the main reason for the lower PTE.

It is also clear that the CE, PTE, and SE (Figure 1 and Table 1) of NC, XY and YT in Jiangxi Province achieved an effective DEA for 2006-2015, which meant the allocation of inputs and outputs had reached their optimum, with technical efficiency and scale efficiency both effective. However, we also obtained non-DEA effective (JJ, JA, YC, FZ, and SR), for which their mean CE was lower than that of Jiangxi Province as a whole (Figure 1A), and *in* a *state* of *diminishing* returns to *scale, except for JJ and YC (*Table 1); likewise, mean PTE for JJ, JA, and SR were lower than Jiangxi Province (Figure 1B) and *in* a *state* of *diminishing* returns to *scale, except for JJ* (Table 1). In contrast NC, PX, XY and YT all have higher PTEs, representing 36.4% of 11 prefecture-level cities (Figure 1B). Both FZ and SR cities had a lower average SE than that of Jiangxi Province (Figure 1C) and were *in* a *state* of *diminishing* returns to *scale* (Table 1), which indicated w*here diminishing returns occur, investment in these cities should be reduced moderately in the future*.

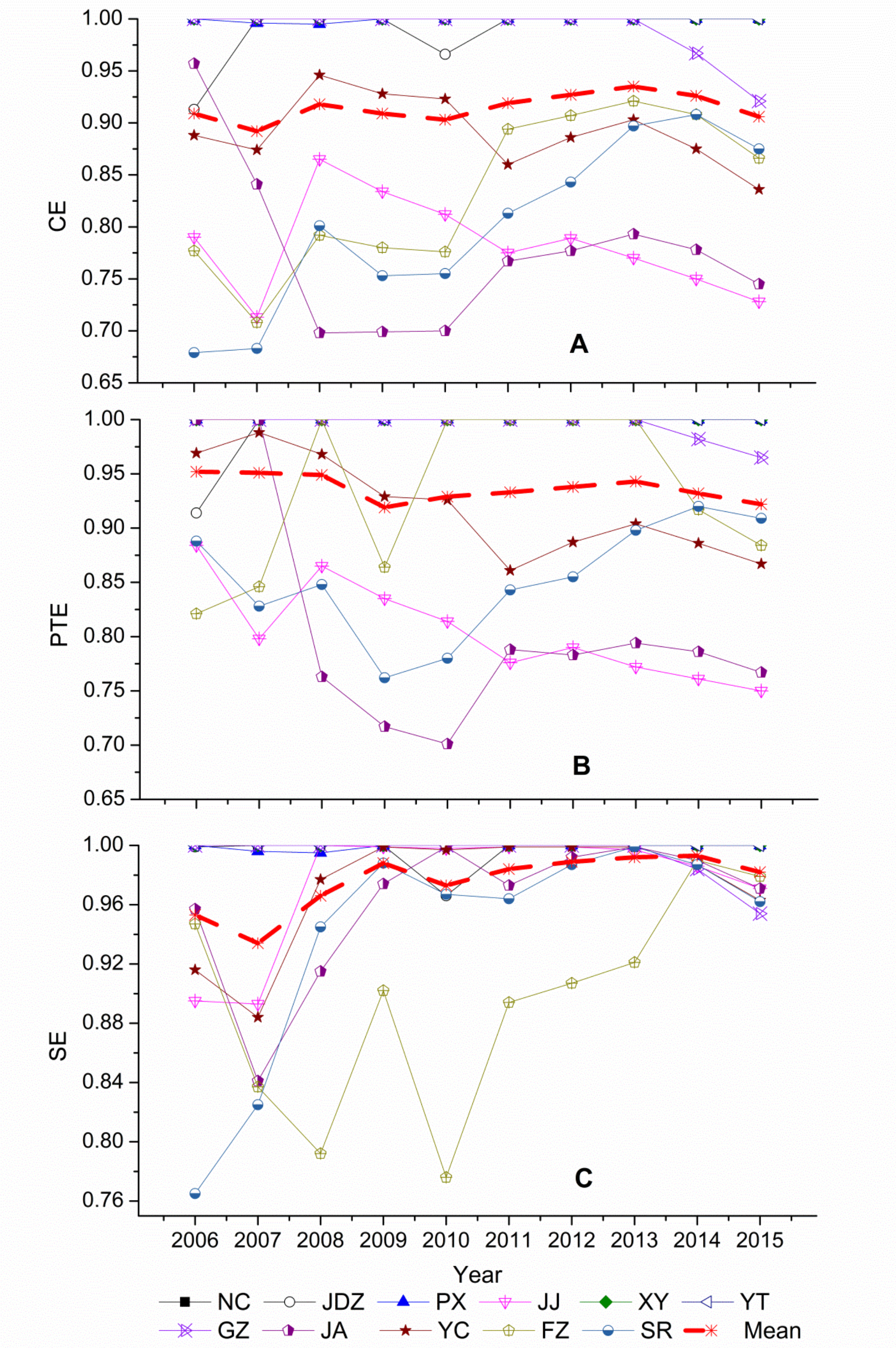

Figure 1. Time-Series Changes of Comprehensive Efficiency (CE), Pure Technical Efficiency (PTE), and Scale Efficiency (SE) in Stage I for the Prefecture-Level Cities of Jiangxi Province, China

Notes. NC, JDZ, PX, JJ, XY, YT, GZ, JA, YC, FZ, and SR refer to the cities of *Nangchang, Jingdezhen, Piangxing, Jiujiang, Xinyu, Yingtan, Ganzhou, Ji'an, Yichun, Fuzhou, and Shangrao,* respectively. The same abbreviations apply in Figure 2, 3, 4 and Table 1, 3, 4.

Table 1. Time-Series Changes of Returns to Scale in Stage I for the 11 Prefecture-Level Cities of Jiangxi Province, China

	NC	JDZ	PX	JJ	XY	YT	GZ	JA	YC	FZ	SR
2006	—	*drs*	—	*drs*	—	—	—	*drs*	*drs*	*drs*	*drs*
2007	—	—	*irs*	*drs*	—	—	—	*drs*	*drs*	*drs*	*drs*
2008	—	—	*irs*	—	—	—	—	*drs*	*drs*	*drs*	*drs*
2009	—	—	—	*irs*	—	—	—	*drs*	*irs*	*drs*	*drs*
2010	—	*drs*	—	*irs*	—	—	—	—	*irs*	*drs*	*drs*
2011	—	—	—	*irs*	—	—	—	*drs*	*irs*	*drs*	*drs*
2012	—	—	—	*irs*	—	—	—	*drs*	*irs*	*drs*	*drs*
2013	—	—	—	*drs*	—	—	—	*drs*	*drs*	*drs*	*drs*
2014	—	—	—	*drs*	—	—	*drs*	*drs*	*drs*	*drs*	*drs*
2015	—	—	—	*drs*	—	—	*drs*	*drs*	*drs*	*drs*	*drs*

Notes. —, *drs*, and *irs* represent constant returns to scale, decreasing returns to scale, and increasing returns to scale, respectively. The same for the Table 3 that follow below.

4.1.2 Stage II: SFA Regression Results

The slack variables, including Total Water (TW), Fixed Assets Investment (FAI), and Labor Force (LF) for the DMU calculated in the first stage were dependent variables in the second stage. According to the results for the SFA regression (Table 2). Both σ^2 and γ *passed the 1% significance test*, and the γ values was close to 1; this indicated that environmental variable and random variable significantly influenced WRUE. Therefore, the selection of the model variables seems to be reasonable, making it necessary to excise and analyze the random and environmental factors of the SFA model. When the regression coefficient is negative, there is an inverse association between environmental variable and the input *slack* variable, meaning that an increase in the former will *lead to* a decrease in the latter. When there values increased, the input *slack* values will be reduced, meaning that WRUE will be improved. Conversely, when the regression coefficient is positive, an increase in a given environmental variable will increase the input *slack* variables, reducing WRUE. *Based on their respective regression coefficients* in Table 2, each environmental variable could be analyzed in detail.

(1) Per capita GDP. *With a* regression coefficient against the LF slack variable that was positive, increasing per capita GDP should lead to an increase in LF investment, which would reduce WRUE. This finding is consistent with that of Radulescu et al. (2018). *The regression coefficients for* per capita GDP *to TW and FAI* slack *variables were negative; hence, when the latter* decrease as per capita GDP increases, the WRUE improves.

(2) Per capita water resources. *All* regression coefficients of this index to the three input *slack* variables were positive, *suggesting more per capita water resources* would increase the inputs of *TW, FAI, and*

LF, leaving WRUE unchanged. Although WRUE was lower in areas *richer water resources* (Zhang & Liang, 2010), because regional *per capita water resources* represents the regional water resources endowment, the greater it is in a region, the richer the water resources there and more of it invested in production activities, inevitably pressuring the decision-making department to invest more into improving WRUE (Ma et al., 2016; Li & Phillips, 2017). However, when the input of various resources has reached its optimum, any increased investment led to decreased in WRUE.

(3) Ratio of PIGDP/TGDP. The regression coefficients for this index to three input slack variables were negative; hence an augmented *ratio of PIGDP/T GDP* is beneficial to lowering the TW, FAI, and LF slack variables. This is because China has introduced several policies on rural land transfer and *agricultural management*, such as "*Decision on Deepening Reforms for Tightening Land Management*" (2004), "Opinions on Guiding the Transfer of Rural Land Management Rights in an Orderly Manner and Developing Appropriated-scale Agricultural Management" (2014), "Opinions on Accelerating the Building of a Policy System and the Cultivation of New Agricultural Business Entities" (2017), among others. Recently, with the gradual acceleration of rural land transfer in China, this *transfer* has fostered the optimization and adjustment of agricultural production structures, *promoting the development of modern intensive agriculture and its scale of management, thus i*mproving *agriculture productivity. Additionally*, this land transfer is also conducive to the *rational* allocation of *rural labor resources and* promotes the transfer of rural labor to more efficient industries. The above results are also considered as more effective for input variable configuration.

(4) Population density. In the regressions with the three input *slack* variables, these coefficients were all negative. Increasing *population density* is conducive to the unified supply of water resources and the unified discharge and treatment of domestic sewage, and it can, to a certain extent, reduce the loss of water resources in the process of transportation (Qin et al., 2017). This is consistent with the compact city development theory (Hofstad, 2012), meaning that the implementation of a compact urban layout within the limits of urban affordability is conducive to improving WRUE and the conservation of water resources. This result is also consistent with Li and Phillips (2017), who found that water utilities with a greater customer density tend to be less inefficient (i.e., more efficient).

Table 2. The Stochastic Frontier Analysis (SFA) Regression Results of Stage II

	Dependent variable		
Independent variable	TW Slack	FAI Slack	LF Slack
Constant	51.7189*** (9.1553)	463.4927*** (68.3379)	532.1322*** (51.7742)
Per capita GDP (Economic level)	-0.0001 (0.0002)	-0.0013* (0.0011)	0.0034*** (0.0010)

P*er capita water resources* (W*ater resource endowment*)	0.0004*	0.0017	0.0050*
	(0.0003)	(0.0043)	(0.0037)
Ratio of PIGDP/T GDP (*Industrial structure*)	-1.2040***	-14.0089***	-14.4178***
	(0.2026)	(2.3412)	(1.9145)
Population density	-0.0348*	-0.4681***	-0.8846***
	(0.0333)	(0.1281)	(0.0902)
σ^2	273.9687***	9035.8872***	20193.3520***
	(27.5871)	(1487.2481)	(1940.4172)
γ	0.9524***	0.7309***	0.9021***
	(0.0098)	(0.0665)	(49.9159)
Log-likelihood function	-328.3730	-604.3488	-599.5599
LR one-sided test	97.70005*	31.1913*	106.4611*

Notes. *, *** represent respectively the significance at alpha levels of 0.1, 0.01. In parentheses is the standard deviation. TW, FAI, and LF represent respectively total water, fixed assets investment, and labour force.

4.1.3 Stage III: The Adjusted DEA Model Results

In Figure 2, unlike Figure 1, the efficiency values for water resource utilization of Jiangxi Province in the first and third stages showed major differences after eliminating the environmental and random variable. On average, CE increased from 0.914 to 0.981, PTE from 0.937 to 0.994, and SE from 0.975 to 0.987, for Jiangxi Province. Hence, the low CE obtained before was caused by an adverse environment or bad luck (or both) but not a low technology management level.

As Figure 2 and Table 3 show, the prefecture-level cities of NC, JDZ, XY, and YT in the third stage during 2007-2015 qualified as *DEA effective*. However, others were non-DEA effective; for example mean values of CE and PTE for JA, YC, and SR were lower than that of Jiangxi Province as a whole (Figure 2A and 2B) and unstable *in their* returns to *scale* (Table 3); importantly, the proportion of higher PTE in all prefecture-level cities rose, from 36.4% to 54.5% (Figure 2B). Except for 2014 and 2015, the SE for FZ was still lower than that of Jiangxi Province (Figure 2C) and i*n* a *state* of *diminishing* returns to *scale* (Table 3).

Comparing Table 3 with Table 1, the prefecture-level cities of NC, XY, and YT in the first and the third stages maintained constant returns to scale. However, only one city was in a state of increasing returns to scale in the first stage, whereas four cities were in the third stage; hence, these the latter cities ought to increase their scale of investment to improve present WRUE. In studying European water utility management, Romano et al. (2017) also found that water utilities receiving lower investments are associated with less resource efficiency and high environmental risks.

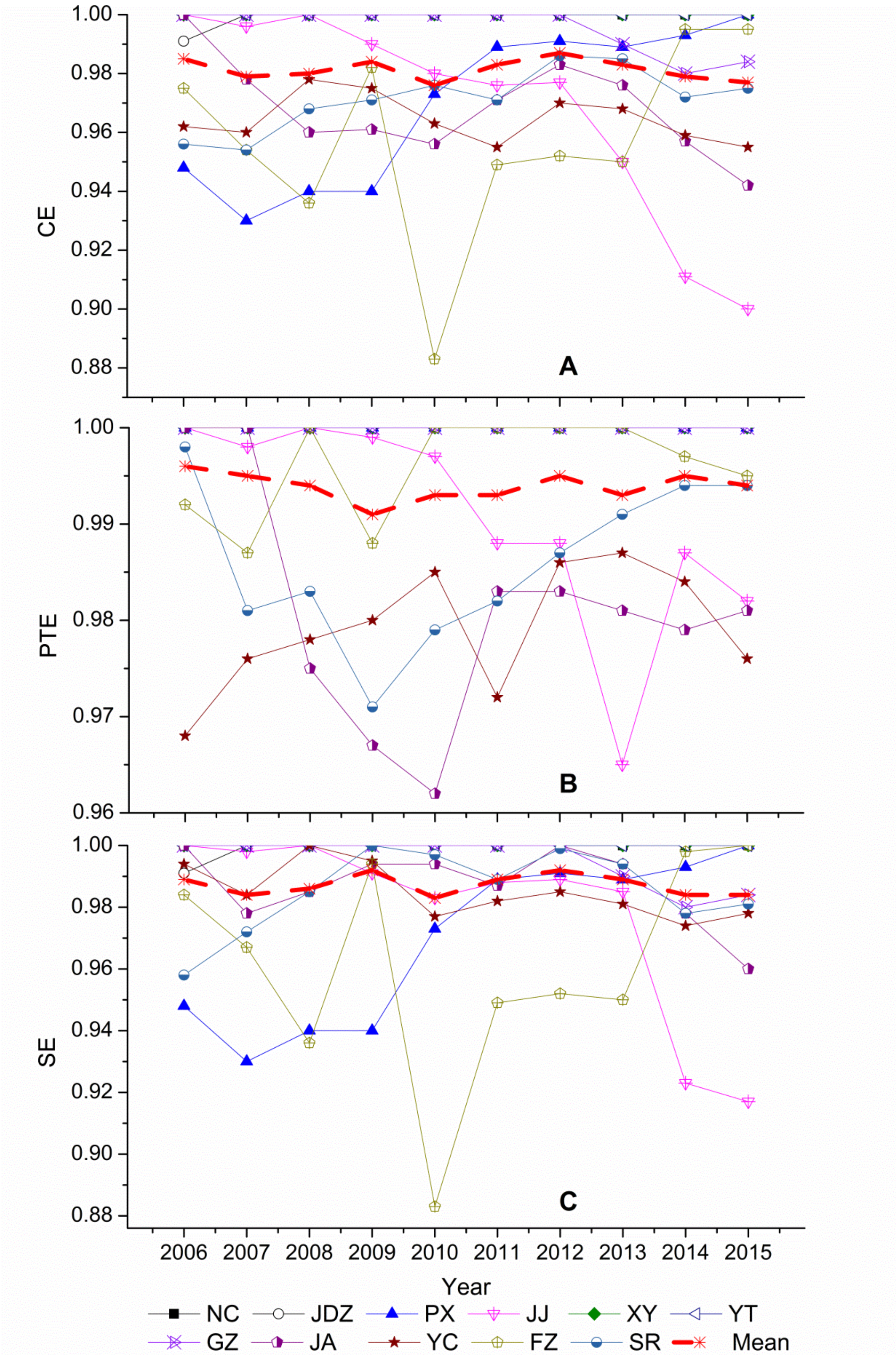

Figure 2. Time-Series Changes of CE, PTE, and SE in Stage III for the Prefecture-Level Cities of Jiangxi Province, China

Table 3. Time-Series Changes of Returns to Scale in Stage III for the 11 Prefecture-Level Cities of Jiangxi Province, China

	NC	JDZ	PX	JJ	XY	YT	GZ	JA	YC	FZ	SR
2006	—	*irs*	*irs*	—	—	—	—	—	*drs*	*drs*	*drs*
2007	—	—	*irs*	*irs*	—	—	—	*drs*	*drs*	*drs*	*drs*
2008	—	—	*irs*	—	—	—	—	*drs*	—	*drs*	*drs*
2009	—	—	*irs*	*irs*	—	—	—	*drs*	*irs*	*drs*	—
2010	—	—	*irs*	*irs*	—	—	—	*irs*	*irs*	*drs*	*irs*
2011	—	—	*irs*	*irs*	—	—	—	*drs*	*irs*	*drs*	*drs*
2012	—	—	*irs*	*irs*	—	—	—	—	*irs*	*drs*	*irs*
2013	—	—	*irs*	*irs*	—	—	*irs*	*irs*	*irs*	*drs*	*irs*
2014	—	—	*irs*	*irs*	—	—	*irs*	*irs*	*irs*	*drs*	*irs*
2015	—	—	—	*irs*	—	—	*irs*	*irs*	*irs*	—	*irs*

4.2 Analysis of CE in the Prefecture-Level Cities of Jiangxi

4.2.1 Spatial Pattern Evolution of CE

For the CE in 2006 (Figure 3), the CE of six of the 11 cities (54.5%) lied on the frontier: NC, JJ, YT, XY, JA, and GZ. Moreover, these cities are relatively concentrated; for example, NC is *adjacent* to JJ, and JA *borders XY and GZ. Additionally*, JDZ city had a higher CE than either *YC and FZ*, *which were only* moderately efficient, while relatively inefficient and scattered cities were Ping Xiang (PX) and Shang Rao (SR) in the central and north of the Jiangxi Province. Five years later, in 2011, the WRUE of five cities lied on the frontier state: NC, YT, JDZ, XY, and GZ. Nevertheless, these cities are relatively scattered. Among them, the value of CE for JDZ had increased, changing from relatively efficient city of 2006 to an *effective DEA*, while those for JJ and YC cities had declined, rendering them relatively *medium-effective* cities. In 2015, the WRUE of five cities also lied on the frontier state (NC, YT, JDZ, XY, and PX). However, now PX replaced GZ as a *DEA effective* city; GZ and FZ achieved relatively high efficiency in this year, while SR was relatively medium-effective, and JJ, JA, and YC cities were all relatively inefficient. Overall, the CE level of water resource utilization for the prefecture-level cities of Jiangxi appears to have undergone a *fluctuating downward trend in the period 2006-2015*. *The changes in DEA effective* cities had a clear spatial pattern over time, going from clear contiguous to a *complicated scatter*, suggesting significant differences among the 11 prefecture-level cities.

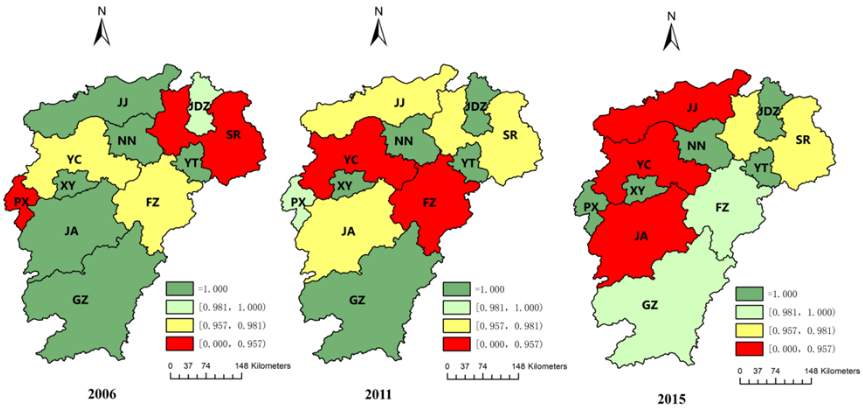

Figure 3. Spatial Pattern Evolution of CE for the Prefecture-Level Cities of Jiangxi Province, China, in Stage III from 2006 to 2015

4.2.2 Average Annual Change in CE

CE represents a comprehensive indicator for WRUE in the prefecture-level cities of Jiangxi Province. From Figure 4, it can be concluded that this indicator changed substantially after the model adjustments made. The *annual average* efficiency of most prefecture-level cities increased after this adjustment, with the indicator increasing by 0.067 on average. Furthermore, the indicators for JJ, JA, YC, FZ, and SR increased from 0.783 to 0.968, 0.776 to 0.968, 0.892 to 0.965, 0.833 to 0.957, and 0.801 to 0.971, respectively. This result reflects the *optimized adjustment* level *of industrial structure* of the different prefecture-level cities, which has an enormous effect on their respective WRUE. Moreover, Figure 4 shows that NC, XY, and YT occupy the frontier of efficiency in water resource utilization. However, PX was no longer at the frontier of CE for the water resources utilization in stage III (i.e., after the eliminating environmental and random variables), which suggests it should increase the *input* scale of its water resource utilization and scale efficiency (Tables 1 and 3). In summary, after the elimination of environmental and random factors, the CE of water resource utilization in 7 of the 11 prefecture-level cities had been greatly increased in third stage when compared with the first stage. The reason was for this was the rise of PTE, but mostly because of the SE growth (Table 3). Therefore, expanding the scale is the key to improving the WRUE.

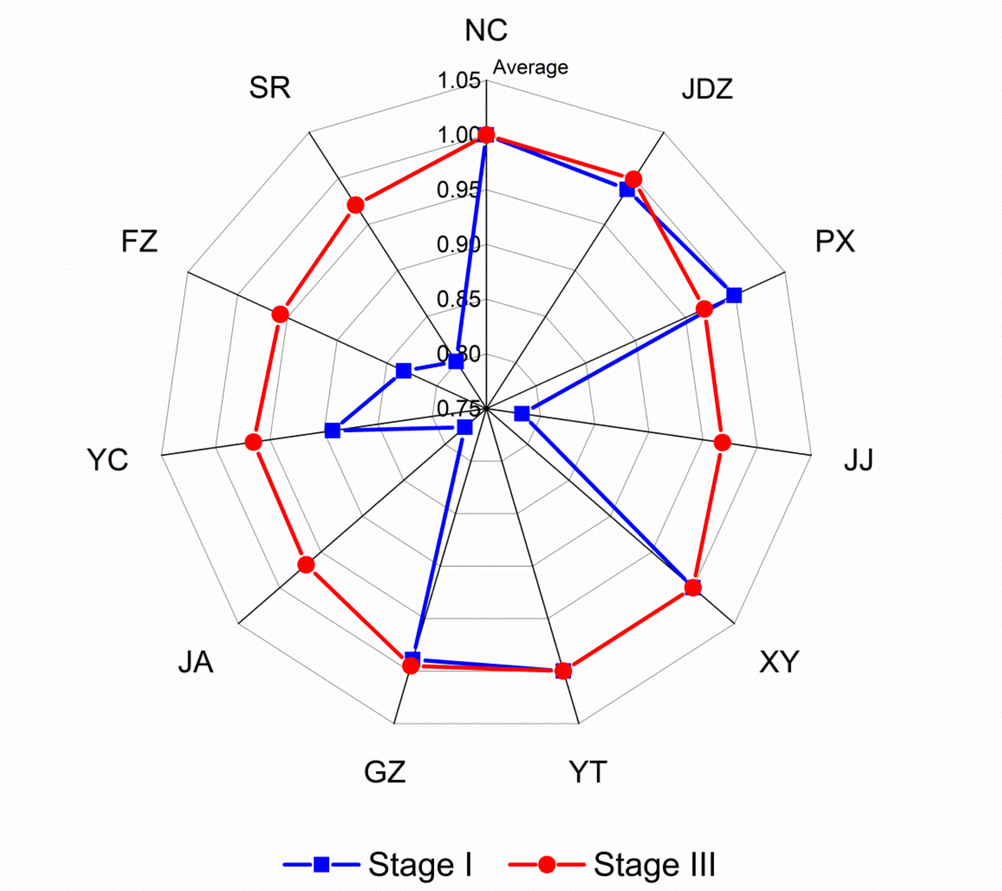

Figure 4. Comprehensive Efficiency for the Prefecture-Level Cities of Jiangxi in Stage I and Stage III

4.3 Analysis of CE in the Stage III Using the Bootstrap DEA Model

The three-stage DEA model has the shortcoming of potential biased efficiency estimates, and the accuracy of its results may be affected by the sampling variation of the estimated frontier (Simar & Wilson, 1998; Balcombe et al., 2008). To avoid these risks, a bootstrap DEA method was opted for, to arrive at unbiased estimations for small sample groups since the total number of prefecture-level cities was low. These results for 2006-2015 were generated in the R software environment, n = 2000 iterations and 95% confidence intervals) and are summarized in Table 4. As it shows, the bias-corrected CE values after were all within the confidence interval, thus confirming the bootstrapped results were accurate and effective. The CE scores after the bias-correction are significantly lower than their counterpart DEA scores and all the average biased errors were > 0, thus indicating that the CE scores through direct use of DEA were higher than the real efficiency scores.

After performing this bias-correction in the bootstrap-DEA, the number of "complete efficiency" scores for the prefecture-level cities of Jiangxi Province is zero. Before being bias-corrected (in stage III), three prefecture-level cities for the period 2006-2015 were found to lie on the frontier achieving a technical efficiency score equal to one, yet afterwards these CE scores were than those stage III DEA scores with no city appearing close to the frontier. This illustrated that even if these prefecture-level cities had reached "complete efficiency" in their water resource utilization, in its conventional (traditional use) meaning, it did not necessarily mean a high level of "absolute efficiency" was achieved. This result agrees with Simar and Wilson (1998), who have seriously questioned the DEA in providing accurate efficiency scores.

Before the bias-correcting adjustment, the top four prefecture-level cities for comprehensive efficiency were NC (1.0000), XY (1.0000), YT (1.0000), and JDZ (0.9990), but after this adjustment the top four were XY (0.9947), NC (0.9931), JDZ (0.9926), and YT (0.9917). Overall, this would suggest there is considerable room for improving WRUE in the prefecture-level cities of Jiangxi Province.

Table 4. Comparison of CE Scores for 11 Prefecture-Level Cities of Jiangxi Province, China, before and after the Bias-Corrected Adjustment to the DEA Model

City	$\hat{\theta}_i$	Rank before bias-corrected	$\theta_i^{'}$	$\hat{bias}_i$	Rank after bias-corrected	LB	UB
NC	1.0000	1	0.9931	0.0069	2	0.9717	1.0000
JDZ	0.9990	4	0.9926	0.0064	3	0.9741	1.0000
PX	0.9690	7	0.9668	0.0022	7	0.9657	0.9819
JJ	0.9680	8	0.9637	0.0043	8	0.9607	0.9796
XY	1.0000	1	0.9947	0.0053	1	0.9818	1.0000
YT	1.0000	1	0.9917	0.0083	4	0.9708	0.9990
GZ	0.9950	5	0.9882	0.0068	5	0.9636	0.9800
JA	0.9680	8	0.9633	0.0047	9	0.9602	0.9710
YC	0.9650	10	0.9614	0.0036	10	0.9610	0.9789
FZ	0.9570	11	0.9554	0.0016	11	0.9550	0.9658
SR	0.9710	6	0.9673	0.0037	6	0.9655	0.9758

Notes. (LB = lower bound of the confidence interval, UB = upper bound of the confidence interval upper bound).

5. Conclusions and Policy Implications

5.1 Conclusions

Water Resource Utilization Efficiency (WRUE) for 11 prefecture-level cities of Jiangxi from 2006 to 2015 were analyzed through a three-stage DEA and bootstrap DEA model, from we drew these four main findings. (1) The Comprehensive Efficiency (CE) of water resource utilization in Jiangxi remains low. From the third-stage DEA model, the CE averaged 0.981, so WRUE could be improved regardless of environmental factors. (2) The results from the second stage of the SFA show that environmental and random variables have a significant influence on WRUE. *Industrial structure and population density were favorable factors to improve* WRUE. After eliminating environmental and random variables, the average CE of Jiangxi Province increased (from 0.914 to 0.981), owing to increases in both PTE (from 0.937 to 0.994) and SE (from 0.975 to 0.987). Of the 11 cities, three of them (NC, XY, YT) had high SE and PTE values, while another three (JDZ, PX, GZ) had low SE and high PTE values. (3) These cities differed significantly in their WRUE, for environmental factors had different effects, and when considered spatially over time, t*he changed DEA effective* cities went from clear contiguous to *complicated scattered pattern*. (4) A higher comprehensive efficiency of *water resource utilization* is obtained from the DEA efficiency model, but this estimate decreased following the bias-correction by the bootstrap-DEA, implying that DEA directly overestimates the WRUE of Jiangxi Province in recent years. Thus, the bootstrap-DEA method can provide more accurate results than the three-stage DEA method.

5.2 Policy Recommendations

According to the above conclusions, some policy recommendations are proposed: (1) Jiangxi province must change the past government assessment system, as well as economic development model that solely pursues GDP growth, and set against the background of huge amounts of undesirable output and low WRUE, explicitly include WRUE into *government performance appraisal systems* and *give* its due emphasis. (2) Jiangxi Province should *further increase* the propagation intensity of *the most stringent water management system,* raise people's *water saving "consciousness"*, further increase the water-saving technology, and encourage and increase investment in new technology, so as to quickly *change local water consumption patterns and* improve WRUE. Crucially, Jiangxi Province should also continuously improve the scale economies of its water resources and achieve optimal water efficiency on both the input and output sides. (3) Jiangxi Province should further *optimize transformation* in its industrial structure and different industrial internal structure, specifically by *optimizing the shoft from* water-intensive into low-water-consuming industries, and also promote high value-added and green industries. Simultaneously, Jiangxi should also formulate industrial development policies closely related to water resources' sustainable utilization, and support the development of industries with low-water consumption intensity. (4) Jiangxi Province should accelerate urban infrastructure construction via the reform of relevant supporting systems, optimize the spatial distribution of urban populations based on water resources and the water environment carrying capacity, fundamentally change the situation of overpopulation in central urban areas, and resolve the water shortage risk caused by high density population agglomeration, so as to promote the coordinated development of these urban population size or density and the corresponding water resources carrying capacity. (5) All prefecture-level cities need to efficiently utilize their limited water resources to create a local resource endowments conditions and aim to improve WRUE from the perspective of water conservation and economic development. Moreover, Jiangxi Province should design and implement appropriate policies regarding water resource input and water saving based on the geographical characteristics of each of its prefecture-level cities. For long-term development cities ought to foster and strengthen *inter-municipal economic cooperation and technological exchange* according their particular conditions, overcome trade protectionism among themselves, gradually shift their water resource utilization efficiency from low to high, and close the gap in WRUE among them. All these are policies could substantially improve water utilization efficiency and promote sustainability.

Acknowledgments

This research was supported by the National Natural Science Foundation of China (Grant # 21367013, 21407069, 71463020), the Jiangxi Provincial Natural Science Foundation of China (Grant # 20142BAB203024, 20151BAB203034), and the Technology Project of Jiangxi Provincial Education Department (Grant # GJJ180265).

Compliance with ethical standards

Conflict of interest

The authors declare that they have no conflict of interest.

References

André, F. J., Herrero, I., & Riesgo, L. (2010). A Modified DEA model to estimate the importance of objectives with an application to agricultural economics. *Omega*, *38*(5), 371-382. https://doi.org/10.1016/j.omega.2009.10.002

Balcombe, K., Davidova, S., & Latrufe, L. (2008). The use of bootstrapped malmquist indices to reassess productivity change findings: An application to a sample of Polish farms. *Applied Economics*, *40*(16), 2055-2061. https://doi.org/10.1080/00036840600949264

Carvalho, P., & Marques, R. C. (2016). Estimating size and scope economies in the Portuguese water sector using the Bayesian stochastic frontier analysis. *Science of the Total Environment*, *544*, 574-586. https://doi.org/10.1016/j.scitotenv.2015.11.169

Charnes, A., Cooper, W. W., & Rhodes, E. (1981). Evaluating program and managerial efficiency: an application of data envelopment analysis to program follow through. *Management Science*, *27*(6), 668-697. https://doi.org/10.1287/mnsc.27.6.668

Dou, Y. (2014). Water resource utilization efficiency in Urumqi based on DEA. *Journal of Arid Land Resources and Environment*, *28*(10), 164-168.

Fried, H. O., Lovell, C. A. K., Schmidt, S. S., & Yaisawarng, S. (2002). Accounting for environmental effects and statistical noise in data envelopment analysis. *Journal of Productivity Analysis*, *17*(1-2), 157-174. https://doi.org/10.1023/A:1013548723393

Hofstad, H. (2012). Compact city development: High ideals and emerging practices. *European Journal of Spatial Development*, *49*, 1-23.

Hu, M. H., Hu, Y. L., Yuan, J. H., & Lu, F. C. (2018). Factor decomposition analysis of industrial wastewater discharge: A case of China's Jiangxi province. *Journal of Economics and Sustainable*

Development, *9*(4), 29-41.

Jondrow, J., Knox Lovell, C. A., Materov, I. S., & Schmidt, P. (1982). On the estimation of technical inefficiency in the stochastic frontier production model. *Journal of Econometrics*, *19*(2-3), 233-238. https://doi.org/10.1016/0304-4076(82)90004-5

Li, F., & Phillips, M. A. (2017). The influence of the regulatory environment on Chinese urban water utilities. *Water Resources Management*, *31*(1), 205-218. https://doi.org/10.1007/s11269-016-1519-z

Ma, H. L., Shi, C. L., & Chou, N. T. (2016). China's water utilization efficiency: An analysis with environmental considerations. *Sustainability*, *8*(6), 516-531. https://doi.org/10.3390/su8060516

Marques, R. C., Berg, S., & Yane, S. (2014). Nonparametric benchmarking of Japanese water utilities: Institutional and environmental factors affecting efficiency. *Journal of Water Resources Planning and Management*, *140*(5), 562-571. https://doi.org/10.1061/(ASCE)WR.1943-5452.0000366

MWR. (2012). Briefings on the opinions of the State Council on implementing the strictest water resources management system. *Ministry of Water Resources of the People's Republic of China*. Retrieved February 17, 2012, from http://www.china.org.cn/china/2012-02/17/content_24664350.htm

Qin, T., Zhang, H. Q., Tong, J. P., & Ma, J. F. (2017). Analysis on threshold effects and dynamic mechanism of water consumption growth in the process of urbanization. *China population, resources and environment*, *27*(5), 45-53.

Radulescu, M., Fedajev, A., Sinisi, C. I., Popescu, C., & Iacob, S. E. (2018). Europe 2020 implementation as driver of economic performance and competitiveness. Panel analysis of CEE countries. *Sustainability*, *10*(2), 566-585. https://doi.org/10.3390/su10020566

Ren, C. F., Li, R. H., & Guo, P. (2017). Two-stage DEA analysis of water resource use efficiency. *Sustainability*, *9*(1), 52-68. https://doi.org/10.3390/su9010052

Romano, G., Guerrini, A., & Marques, R. C. (2017). European water utility management: promoting efficiency, innovation and knowledge in the water industry. *Water Resources Management*, *31*(2), 2349-2353. https://doi.org/10.1007/s11269-017-1697-3

Simar, L., & Wilson, P. W. (1998). Sensitivity analysis of efficiency scores: how to bootstrap in nonparametric frontier models. *Management Science*, *44*(1), 49-61. https://doi.org/10.1287/mnsc.44.1.49

Simar, L., & Wilson, P. W. (1999). Some problems with the Ferrier/Hirschberg bootstrap idea. *Journal of Productivity Analysis*, *11*(1), 67-80. https://doi.org/10.1023/A:1007735422028

Simar, L., & Wilson, P. W. (2000a). Statistical inference in nonparametric frontier models: The state of the art. *Journal of Productivity Analysis*, *13*(1), 49-78.

Simar, L., & Wilson, P. W. (2000b). A general methodology for bootstrapping non parametric frontier models. *Journal of Applied Statistics*, *27*(6), 779-802. https://doi.org/10.1080/02664760050081951

Simar, L., & Wilson, P. W. (2008). Statistical interference in non-parametric frontier models: recent developments and perspectives. In H. Fried, Lovell, CAK., & S. Schmidt (Eds.), *The measurement of productive efficiency and productivity change*. Oxford University Press, New York. https://doi.org/10.1093/acprof:oso/9780195183528.003.0004

Sun, C. Z., & Zhao, L. S. (2013). Water resources utilization environmental efficiency measurement and its spatial correlation characteristics analysis under the environmental regulation background. *Economic Geography*, *33*(2), 26-32.

Sun, C. Z., Zhao, L. S., Zou, W., & Zheng, D. F. (2014). Water resource utilization efficiency and spatial spillover effects in China. *Journal of Geographic Sciences*, *24*(5), 771-788. https://doi.org/10.1007/s11442-014-1119-x

Wang, X., & Lu, Q. (2014). The empirical analysis of regional differences in Chinese agricultural water use efficiency and convergence test. *Soft Science*, *28*(11), 133-137.

Wang, Y. S., Xu, H., & Bian, Y. W. (2016). Industrial water use system efficiency evaluation: a two-stage DEA model considering pollutants disposability. *Chinese Journal of Management Sciences*, *24*(3), 169-176.

Wang, Y., Bian, Y., & Xu, H. (2015). Water use efficiency and related pollutants' abatement costs of regional industrial systems in China: A slacks-based measure approach. *Journal of Cleaner Production*, *101*, 301-310. https://doi.org/10.1016/j.jclepro.2015.03.092

Worthington, A. C. (2014). A review of frontier approaches to efficiency and productivity measurement in urban water utilities. *Urban Water Journal*, *11*(1), 55-73. https://doi.org/10.1080/1573062X.2013.765488

Xie, Y. J., & Zhou, Y. (2014). Study on the design of water *rights registration* scheme in Jiangxi province. *Water Resources Development Research*, *10*, 70-73.

Zeng, S. H., Hu, M. M., & Su, B. (2016). Research on investment efficiency and policy recommendations for the culture industry of China based on a three-stage DEA. *Sustainability*, *8*(4), 324-338. https://doi.org/10.3390/su8040324

Zhang, L. X., & Liang, J. (2010). Effect of the regional resource endowment on resource utilization efficiency. *Journal of Natural Resources*, *25*(8), 1237-1247.

Zhang, Y., & Bartels, R. (1998). The effect of sample size on mean efficiency in DEA with an application to electricity distribution in Australia, Sweden and New Zealand. *Journal of Productivity Analysis*, *9*, 187-204. https://doi.org/10.1023/A:1018395303580

Zhao, C. H., Zhang, H. N., Zeng, Y. R., Li, F. Y., Liu, Y. X., Qin, C. J., & Yuan, J. H. (2018). Total-factor energy efficiency in BRI countries: An estimation based on three-stage DEA model. *Sustainability*, *10*(1), 278-292. https://doi.org/10.3390/su10010278

Zhou, H., Huang, J. J., & Yuan, Y. B. (2017). Analysis of the spatial characteristics of the water usage patterns based on ESDA-GIS: an example of Hubei province, China. *Water Resources Management*, *31*(5), 1503-1516. https://doi.org/10.1007/s11269-017-1591-z