Benchmarking on Water Resource Utilization Efficiency of Prefecture-Level Cities in Jiangxi, China: A Bootstrap-DEA Approach with Three-Stage DEA Models

Mianhao Hu[1], Yunling Hu[1], & Juhong Yuan[2]

[1] Institute of Ecological Economics, Jiangxi University of Finance & Economics, Nanchang, P. R. China

[2] Institute of Landscape and Plant Resources, Jiangxi University of Finance & Economics, Nanchang, P. R. China

Correspondence: Mianhao Hu, Institute of Ecological Economics, Jiangxi University of Finance & Economics, Nanchang 330032, P. R. China. Tel: 086-791-8381-0553. E-mail: yankeu1@163.com

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Abstract

China has long been adopted traditional data envelopment analysis (DEA) models to measure water resources utilization efficiency of different provinces and cities without bias correction of efficiency scores. In this study, the Bootstrap-DEA approach embedded 3-stage DEA models was introduced to analyze the comprehensive efficiency of water resources utilization in the different prefecture-level cities Jiangxi and tried to improve the application of this method for benchmarking and inter-regional research. It is found that the bias corrected efficiency scores of Bootstrap-DEA differ significantly from those of the traditional DEA model, which implies that Chinese researchers need to update their DEA models for more scientific calculation of water resources utilization efficiency scores. This research has helped narrow the inter-regional gap in the comprehensive efficiency measurement and improvement of water resources utilization. It is suggested that Bootstrap-DEA embedded 3-stage DEA models be widely applied into afterward research to measure comprehensive efficiency of water resources utilization in regional inter-city so as to better serve for efficiency improvement and related decision making.

Keywords: Comprehensive Efficiency, Water Resource Utilization, Bootstrap-DEA, Benchmarking

1. Introduction

Jiangxi Province is rich in water resources, but the spatial distribution of water resources is extremely uneven. Drought and flood disasters occur frequently in Jiangxi Province (Ye & Meng, 2015). Furthermore, inefficiency of water use further adds to the problem of water environment in Jiangxi Province. According to Jiangxi Water Resources Bulletin, 43.91 billion t of water was discarded in 2017, as compared to 32.79 billion t in 2000, which suggests an increase in the quantity of discarded water, by 33.91%, during these years. At present, the contradiction between supply and demand of water resources is prominent in Jiangxi Province. Therefore, utilization efficiency of water resources becomes imperative for Jiangxi Province to maintain a sustainable water supply.

There have been many domestic and overseas research studies on the efficiency of water resources utilization with different models. Sala-Garrido et al. (2012) used bootstrap technology to improve the DEA model, estimate the sewage disposal efficiency. Sun et al. (2013) used undesirable output radial direction DEA model to measure the water resources utilization relative environmental technology efficiency of 31 provinces in China. Sun et al. (2014) used the relaxation and non-radial undesirable output SBM model to measure the water resource utilization efficiency of 31 provinces in China. Zhang et al. (2015) used the SBM-DEA model evaluate urban water resource utilization efficiency of 316 cities in China. Han & Su (2015) evaluate the water resources use efficiency of 9 cities in Fujian Province using DEA-BCC model and Malmquist total factor productivity index method. Ma et al. (2016) estimated China's water utilization efficiency using the directional distance function to take into account the environmental degradation affecting the economy. Lu & Xu (2017) used a three-stage DEA model and the Malmquist index method to measure the water resources utilization efficiency of 11 provinces and cities in the Yangtze River economic belt. Most of the above models are based on the DEA model, and the decision-making units (DMUs) operating for the frontier in DEA model would be considered as efficient. However, in the real situation, all the DMUs are subject to environment and random factors, which implies that their efficiency scores will fall into a fluctuating range. To solve the problem, the Bootstrap method is introduced in the efficiency measurement of DMUs based on DEA, in order to correct the bias of efficiency scores and to calculate their confidential intervals, lower and upper bounds, and so on (Simar & Wilson, 1998, 2000), which will help improve the accuracy of DEA efficiency scores. Although the Bootstrap-DEA has been considered as a milestone in international world in relative efficiency and productivity measurement, most of the Chinese studies have long been focused on the measurement of water resource utilization efficiency in itself and few research has been done on how to utilize these results to conduct benchmarking for regional inter-city efficiency improvement. Therefore, this study is based on the previous research to take the first initiative to introduce the Bootstrap-DEA approach embedded into 3-stage DEA models to measure the comprehensive efficiency of water resource utilization in the prefecture-level cities of Jiangxi, and explore the benchmarking mechanism for further efficiency improvement. It can also act as a preliminary study in the methodological improvements for the reference of other Chinese researchers to be applied in the future.

2. Methodology

2.1 Bootstrap Three-Stage Procedure

At the first stage, the water resource utilization efficiency (WRUE) of prefecture-level cities under the impacts of exotic environmental factors and statistical noise are calculated by the input-oriented BCC model, which are named as comprehensive efficiencies (CE) in this study. At the second stage, the slack component of each input variable is decomposed into three categories, including environmental values, managerial inefficiency, and statistical noise, and the adjusted input variables values of each prefecture-level cities are obtained through eliminating the impacts of statistical noise and environmental values. At the third stage, the WRUE of prefecture-level cities are reevaluated while using the input-oriented BCC model, which is the same as the model that was used at the first stage but inputting the adjusted input variables values that were obtained from the second stage to calculate the real CE of water resource utilization for prefecture-level cities. Finally, on the basis of the third stage, the Simar & Wilson (1998, 2000, 2008) procedure is used to bootstrap the DEA scores with a truncated bootstrapped regression (Wijesiri et al., 2015).

Stage 1

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 and Cooper) 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):

$$Min[\theta - \varepsilon(e^T s^- + e^T s^+)] \qquad s \cdot$$

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

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).

Stage 2

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):

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

where S_{ni} is the slack variable of the I^{th} sample investment in the n^{th} DMUs (decision making units); $z_i = (z_{1i}, z_{2i},..., z_{ki})$ 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 $v_{ni} \sim N(0, \sigma_{vn}^2)$ 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:

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

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:

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

Stage 3

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.

2.2 Bootstrap-DEA Based Procedure

On the basis of the adjusted inputs values that were calculated at the 3-stage, as well as the initial outputs that were utilized at the first stage, the input-oriented BCC model could calculate the real CE in the prefecture-level cities of Jiangxi, eliminating the influences of statistical noise and exotic environmental values. In this study, the bootstrap-DEA method, of sampling with replacement, with B = 3000 bootstrap replications and confidence intervals of 95%, was applied to bias-corrected estimates of CE. The following steps were taken for this bootstrap DEA estimation (Simar & Wilson, 1998, 1999, 2000):

(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 $x_i^* = \hat{\theta}_i x_i / \hat{\beta}_i^*$ 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 ($\theta_i^{'}$).

$$\begin{cases} \widehat{bias}_i = \frac{1}{B}\sum_{b=1}^{B} \hat{\theta}_{ib}^* - \hat{\theta}_i \\ \theta_i' = \hat{\theta}_i - \widehat{bias}_i \qquad i = 1, \quad 2, \quad \cdots \quad N \end{cases} \quad (5)$$

2.3 Benchmarking Method

Based on the idea of efficiency benchmarking (Nuti et al., 2009; Li & Dong, 2012) in our study, the different color definitions in bar chart were applied to depict standardized efficiency values. That means, if a standardized efficiency value is regarded as excellent performance, dark green will be applied in the benchmarking bar chart; if it is regarded as good performance, light green will be applied; and if poor performance is regarded, yellow will be applied; In practice, prefecture-level cities colored with yellow would have ample scope for improvement.

3. Variable Selection and Data Sources

3.1 Selection of 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. The descriptive statistics of the selected variables are indicated in Table 1.

Table 1. Descriptive statistics of inputs and outputs

Variable	Mean	Median	Std deviation	Minimum	Maximum
Inputs					
1. Total water	22.24	24.31	11.91	6.22	45.10
2. Fixed assets investment	788.87	648.98	671.11	60.58	4000.07
3. Labor force	237.19	258.70	135.11	62.31	547.80
Outputs					
4. GDP	789.79	608.89	603.24	143.21	3488.28
5. COD	31000.25	26007.50	16380.96	12900.00	82937.00

Note: GDP and COD represent respectively gross domestic product (GDP) and chemical oxygen demand (COD).

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. Environmental factors are divided into three kinds: natural, economic, and social. In this study, per 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.

3.3 Data Sources and Analysis

All the above data were derived from the Jiangxi Provincial Statistical Yearbook and the Jiangxi Province Water Resources Bulletin. The output oriented efficiency scores of the 11 prefecture-level cities were calculated using R software and FEAR package (Wilson, 2008). The efficiency scores before bias correction would return to Farrell scores (Farrel, 1957), and the bias corrected ones after Bootstrap-DEA would return to scores on the basis of Shephard's output distance functions, bias, lower bound, and upper bound (Shephard, 1970). Then the bias corrected efficiency scores are further used in a bar chart for benchmarking.

4. Results and Discussion

4.1 Bootstrap-DEA Efficiency Scores

Table 2 is a comparison of the efficiency scores with and without bias corrections. It can be seen that, in the traditional BCC model, 6 prefecture-level cities of Jiangxi Province have efficiency scores of 1, which means that these prefecture-level cities realize high efficient utilization of water resources, and do not need to improve their technical efficiency. Maintaining current status would be their best choice. As the volumes of inputs and outputs in each of the prefecture-level cities are different and the water resources utilization for prefecture-level cities are subject to environmental and random factors, it is obvious that there should be some efficiency bias to explain their difference, as is evidenced in the Bootstrap-DEA results in Table 2.

As can be seen from Table 2, it was easy to find that all the bias corrected efficiency scores are lower than those before correction, implying that the Bootstrap-DEA method has improved the accuracy of the estimated efficiency scores. The model is hence more precise than traditional DEA models. Moreover, take the small sample as an example, the application of traditional DEA models is limited, since one of the basic conditions to use DEA requires that the number of DMUs should be 3 times more than the total number of input and output indicators (O'Neill et al., 2008). Nevertheless, the Bootstrap-DEA method can help break the bottleneck by repeated sampling (usually 2000 times) to increase the number of DMUs, in order to make the estimated efficiency scores much closer to their real scores. Because few studies in many Chinese studies have applied Bootstrap-DEA method (Li, 2014; Yu et al., 2017), so that the number of DMUs did not meet the minimum requirement, in future study of regional WRUE in China, Bootstrap-DEA method can be widely used to provide more reliable results for efficiency improvement and decision making.

Table 2. Comparison of efficiency scores in 2015 with and without bias correction

City	Efficiency scores (bias not corrected)	Efficiency scores (bias corrected)	Bias	Lower bound	Upper bound
NC	1.00000	0.99187	0.00813	0.97530	1.00000
JDZ	1.00000	0.99186	0.00814	0.97519	1.00000
PX	1.00000	0.99195	0.00805	0.97501	1.00000
JJ	0.98197	0.97743	0.00454	0.96850	0.98176
XY	1.00000	0.99210	0.00790	0.97545	1.00000
YT	1.00000	0.99198	0.00802	0.97514	1.00000
GZ	1.00000	0.99652	0.00348	0.98900	1.00000
JA	0.98092	0.97708	0.00384	0.97053	0.98073
YC	0.97650	0.97347	0.00303	0.96797	0.97629
FZ	0.99529	0.99078	0.00451	0.98014	0.99507
SR	0.99403	0.99105	0.00298	0.98518	0.99381

Note: NC, JDZ, PX, JJ, XY, YT, GZ, JA, YC, FZ, and SR refer to the cities of Nangchang city, Jingdezhen city, Piangxing city, Jiujiang city, Xinyu city, Yingtan city, Ganzhou city, Ji'an city, Yichun city, Fuzhou city, and Shangrao city, respectively.

4.2 Efficiency Benchmarking of Prefecture-Level Cities

CE represents the comprehensive indicator for WRUE in the prefecture-level cities of Jiangxi and is analyzed first. To further make the results visual for performance evaluation of prefecture-level cities CE in 2015, they are further benchmarked in Figure 1, in which the new scores were originated from efficiency scores multiplied by 100. The average score of 11 prefecture-level cities is 98.78, among them 3 have scores lower than 98.78 and 8 have scores greater than 98.78. The prefecture-level cities can be classified into 3 groups, where 1 prefecture-level cities fall into the first group (dark green), representing excellent performance; 7 prefecture-level cities falls into the second group (light green), representing good performance; and 1 prefecture-level cities fall into the third group (yellow), which must improve their performance.

Although it can effectively help regional government to identify best practices for other peer region to learn from, efficiency benchmarking in Chinese studies has seldom been used for further improvements. In addition, the benchmarking results of urban WRUE can act as a basis to further construct an inter-region government cooperation mechanisms for water conservation management to learn and make continuous and sustainable improvements (Song & He, 2014; Rani & Singh, 2018). Furthermore, in some context, such as when the environment factors do not change substantially, researchers can regard the DMUs in different periods as different DMUs in one period. In this way, the efficiency scores via Bootstrap-DEA method can be applied in the horizontal and longitudinal benchmarking. However, China has yet to learn more from international experience to build its information systems, performance evaluation systems, management by objectives systems for urban water resource, etc, to enable benchmarking among regions with the support of a performance evaluation agency (Song & Gao, 2017).

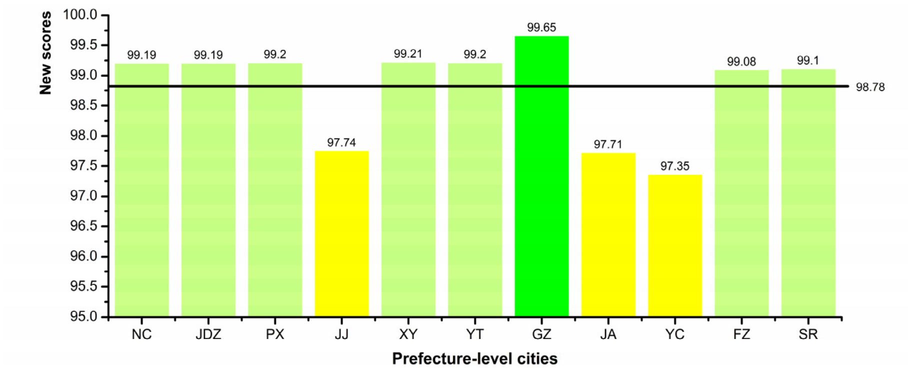

Figure 1. Efficiency benchmarking for prefecture-level cities after bias corrected in 2015. NC, JDZ, PX, JJ, XY, YT, GZ, JA, YC, FZ, and SR refer to the cities of Nangchang city, Jingdezhen city, Piangxing city, Jiujiang city, Xinyu city, Yingtan city, Ganzhou city, Ji'an city, Yichun city, Fuzhou city, and Shangrao city, respectively

4.3 Efficiency Benchmarking of Region

Regional classification is an effective measures to improve the scientific and targeted management of water saving, and improve the comparability and accuracy of comparability and accuracy of regional WRUE benchmarks. On the basis of geographical division, Jiangxi province is divided into five regions, including the eastern, southern, central, western, and northern; among which the eastern includes Shangrao city, Yingtan city and Fuzhou city, the southern includes Ganzhou city, the central includes Nangchang city, the western includes Yichun city, Xinyu city, Piangxing city and Ji'an city, and the northern includes Jiujiang city, Jingdezhen city (see Figure 2).

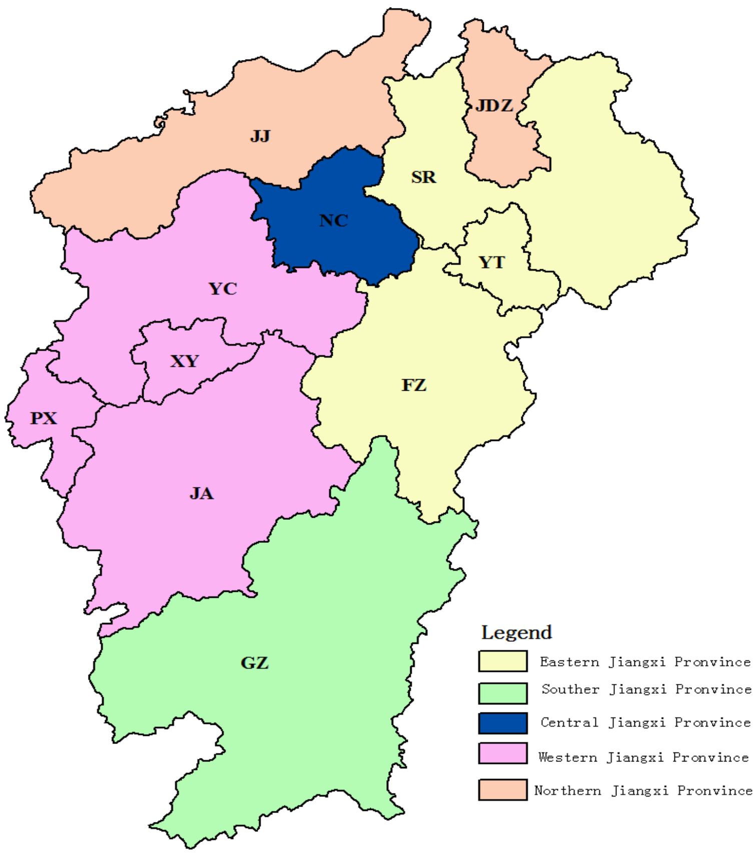

Figure 2. Diagram of region division in Jiangxi Province, China. NC, JDZ, PX, JJ, XY, YT, GZ, JA, YC, FZ, and SR refer to the cities of Nangchang city, Jingdezhen city, Piangxing city, Jiujiang city, Xinyu city, Yingtan city, Ganzhou city, Ji'an city, Yichun city, Fuzhou city, and Shangrao city, respectively

According to the efficiency value of each city in Table 2 and combine each prefecture-level city located region, the visual results of efficiency benchmarking for regional CE in 2015 were shown in Figure 3, in which the new scores were originated from the average efficiency scores of all the cities in the region multiplied by 100. The average score of 5 region is 98.96, among them 2 have scores lower than 98.96 and 3 have scores greater than 98.96. The five region can be classified into 3 groups, where 1 region fall into the first group (dark green), representing excellent performance; 2 region falls into the second group (light green), representing good performance; and 2 region fall into the third group (yellow), which must improve their performance (Figure 3). As can be seen from Figure 3, the WRUE was higher in southern Jiangxi Province, followed by the eastern and central Jiangxi Province, while the WRUE of western and northern Jiangxi Province were relatively low. From Table 2 and Figure 1, the WRUE of the whole western Jiangxi Province were lowered by Yichun city, while the WRUE of the whole northern Jiangxi Province were lowered by Jiujiang city.

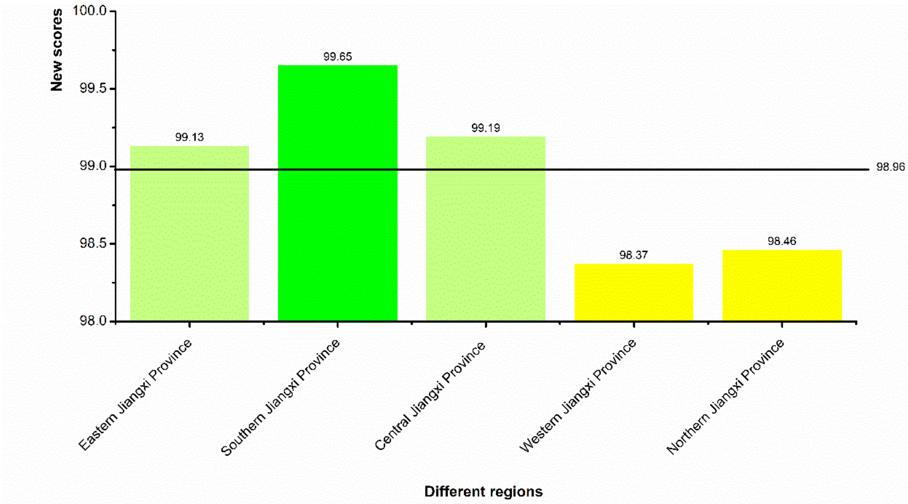

Figure 3. Efficiency benchmarking for different region of Jiangxi Province after bias corrected in 2015

5. Conclusions and Future Research

In this study, with DEA efficiency method, the higher comprehensive efficiencies scores of water resource utilization is obtained, while the efficiency scores decreases after the bias corrected by Bootstrap method, implying DEA direct results overestimate the water resource utilization efficiency (WRUE) of Jiangxi Province for recent years, while the bootstrap-DEA method can provide more accurate results than the three-stage DEA method. Moreover, we have first introduced the Bootstrap-DEA approach based on three-stage DEA models to measure and benchmark the comprehensive efficiency of water resource utilization for prefecture-level cities in Jiangxi Province. However, more researches need to be conducted in the different prefecture-level cities of other province in China.

The comprehensive efficiencies of water resource utilization for prefecture-level cities of Jiangxi Province was higher as a whole, but the polarization of efficiency benchmarking values was serious. Three of 11 prefecture-level cities have scores lower than average score (98.78), while only 1 prefecture-level city was well above average score in this study. Thus, it is necessary to promote the continuous improvement of water resource utilization efficiencies for prefecture-level cities of Jiangxi Province.

In addition, there is a big difference between efficiencies values of water resource utilization in the eastern, southern, central, western, and northern regions. The WRUE was higher in southern Jiangxi Province, while the WRUE of western Jiangxi Province was relatively low. This indicated that the western region needs many improvements in water resource utilization and management. However, our benchmarking research on water resource efficiency has laid a foundation for benchmarking research on water resource utilization efficiency in other provinces and cities in China.

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Conflict of interests

The authors declare that there is no conflict of interests regarding the publication of this paper.

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