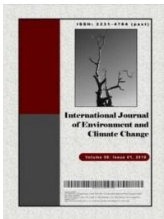

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Regional Environmental Efficiency Based on a Modified Proportional DEA Model

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Authors' contributions

This work was carried out in collaboration between both authors. Author YX designed the study, performed the statistical analysis, wrote the protocol and wrote the first draft of the manuscript. Author WW managed the analyses of the study and the literature searches. Both authors read and approved the final manuscript.

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ABSTRACT

With the increased attention paid to environmental and ecological issues in China, many methods have been used to evaluate the performance of ecological conservation. Scholars have evaluated environmental efficiency in the production process with undesirable outputs, and used a data envelopment analysis (DEA) model for further examination. However, previous studies do not detail the influence of uncertain factors on undesirable outputs, such as environmental capacity and risk attitude. Therefore, this study proposes and applies a modified proportional DEA model to evaluate the environmental efficiency of various textile and clothing companies located around the main stem and tributaries of the Yangtze River. The empirical results indicate that this model is more suitable to evaluate the environmental efficiency of companies in these acutely polluted regions. Based on these findings, we suggest considering environmental capacity and risk attitude in ecological conservation policies to improve environmental efficiency.

Keywords: Data envelopment analysis; proportional model; environmental efficiency; environmental capacity; risk attitude.

1. INTRODUCTION

Environmental issues, and specifically those resulting from globalisation and the acceleration of industrialisation, pose a significant threat to human survival and development. This is especially the case in China, a developing country that over-emphasises advancing the

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economy, and ignores environmental protection. Consequently, problems like soil desertification, water quality deterioration, and air pollution are becoming increasingly serious. These environmental issues endanger citizens' health and quality of life, and decrease the economic gains achieved through the Reform and Opening-Up periods.

In 2016, 'smog' once again became an annual research keyword, after Beijing, Tianjin, Hebei, and many cities in Henan, Shandong, Shanxi, and even Guangdong, were shrouded in heavy smog on five separate occasions in December 2016 according to the 'Report on the State of the Environment in China' [1]. Further, the longest smog duration records were broken in many cities.

Many emergency measures have been proposed to solve air pollution, such as an 'odd–even' car ban, limiting production, or shutting down enterprises. While these measures partially decrease pollutant emissions, they have an insignificant effect on improving environmental quality. The key to completely solving such environmental issues involves constructing an ecological civilisation. Currently, the Central Committee of the Communist Party of China and the State Council of China have promoted the development of this 'civilisation' as China's national strategy. The General Secretary of the Communist Party of China Jinping Xi noted in December 2016 that all governmental departments should conform to an ideal wherein clean mountains and water are considered invaluable assets. Furthermore, he noted that these departments should work diligently to construct an ecological civilisation that addresses serious ecological and environmental problems that adversely affect human lives. According to the 13th Five-Year Plan for Ecological and Environmental Protection (2016–2020), which the State Council of China published on 5 December 2016, the key points that underline an ecological civilisation include: control of pollutant emissions, promotion of industrial restructuring, adjusting national energy structures, optimising industrial layouts, and evaluating the performance of ecological conservation.

Almost all regions within China actively promote the progress of ecological conservation under a unified arrangement with the State. Subsequently, a scientific evaluation system should first be built to evaluate officials' performance in ecological conservation. The Chinese government currently uses a comprehensive target system for economic and social development to evaluate each region's performance of ecological conservation, which includes analysing indicators like resource consumption, environmental damage, and environmental benefits. The target evaluation method is simple and clear, but it is relatively subjective; it cannot reveal the concrete relationships between inputs and outputs of different decision-making units (DMUs) during the production process. Therefore, it is of great significance to discover a scientific method to measure regional environmental efficiency—a vital index that can truly reflect performance of ecological conservation. This method can then be used to guide the reconstruction of the ecological civilisation, reduce discharge of contaminants, improve efficiency in energy use, and ultimately achieve sustainable development in society.

The World Business Council for Sustainable Development defines environmental efficiency through the delivery of competitively priced goods and services that satisfy human needs and bring quality of life. Simultaneously, it must progressively decrease ecological impacts and resource intensity throughout a life-cycle to a level that at least parallels the planet's estimated carrying capacity. In short, environmental efficiency is concerned with creating more outputs with fewer inputs [2]. The most widely used environmental efficiency evaluation method is the data envelopment analysis (DEA) model. Many different methods have been proposed,which are related to the following categories. The first category is the traditional DEA model ignoring undesirable outputs [3], but it neglects the different natures of undesirable outputs. The second category is treating the undersirable outputs as inputs for processing [4][5]], but it fails to reflect the real production process. The third category is transforming an undesirable output into a normal output and then evaluating the environmental efficiency with the traditional DEA model [6,7], but it can only be solved under classification invariance because of the strong convexity constraints. The fourth category is based on Shephard's distance function and the weak disposability of pollutants.when a especially direction for DMUs is set, undesirable outputs reduced and desirable outputs increased at the same time [8]. None of the aforementioned studies are thus able to describe the characteristics of undesirable outputs. However, we modified the current proportional DEA model in this paper by considering uncertain factors (such as environmental capacity and risk attitude) to evaluate the environmental efficiency of textile and clothing companies in the main stem and tributaries of the Yangtze River.

2. METHODOLOGY

The DEA model is a new interdisciplinary theory based on economics, management science, and operational research. It was first proposed by Charnes, Cooper, and Rhodes [9]. It uses a mathematical plan model to evaluate the relative efficiency of production divisions or DMUs with the same types of inputs and outputs. This model is advantageous because it ignores the relationships between inputs and outputs. It is unnecessary to estimate the value of related parameters, which avoids the effects of subjective factors on the evaluation results. Therefore, the DEA model has quickly become a requisite mathematical tool of analysis in system sciences and management engineering. The original DEA model is the Charnes–Cooper–Rhodes (CCR) model, which evaluates DMUs' comprehensive efficiency in the case of a constant output. Later, Banker, Charnes and Cooper proposed the Banker–Charnes–Cooper (BCC) model to evaluate DMUs' efficiency with a variable output by adding the constraint condition

$$\sum_{j=1}^{n} \eta_j = 1$$

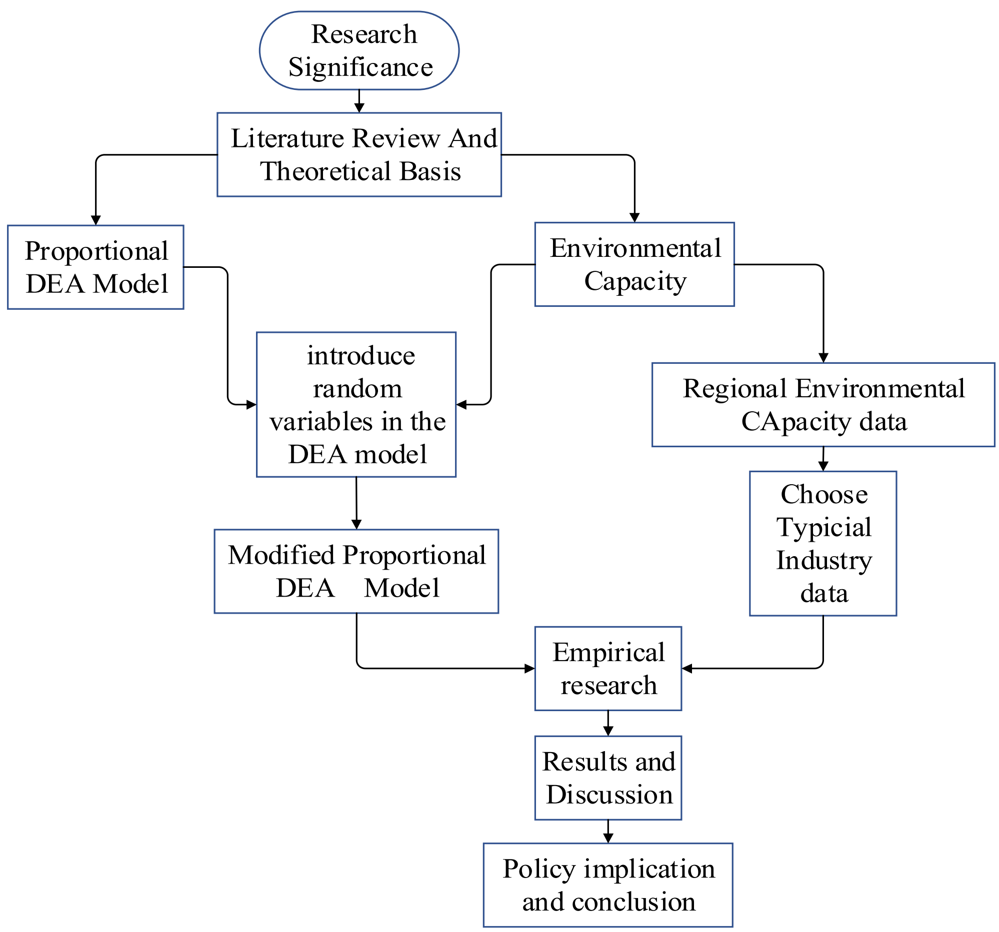


Fig. 1. The flowchart of study framework and logic flows

$$\min\theta(s.t.\ \sum_{j=1}^{n}\eta_j x_{ij}+s^{-}=\theta x_0$$

$$\sum_{j=1}^{n}\eta_j y_{ij}-s^{+}=y_0$$

$$s^{-},\ s^{+},\ \eta_j\geq 0,\ j=1,2,\ \ldots,\ n) \qquad (1)$$

where θ is the scalar quantity; x_{ij} and y_{ij} are the inputs and outputs vectors, respectively; n_j is the weighted vector; and x_0 and y_0 are the actual respective inputs and outputs of DMUs. Further, s^{-}, s^{+} are the relaxing variables, and θ is the solved result [10].

Please note that, although the CCR and BCC models aim to achieve the maximum outputs with minimum inputs, they are not perfectly fit to evaluate ecological efficiency. This is because the original DEA model notes that, liquid waste, exhaust gas, and waste residue, which are unavoidable in industrial production and considered undesirable outputs, increase with an increasing expected output. This results in decreasing efficiency. As a result, You and Yan proposed a proportional DEA model to solve for undesirable outputs based on previous studies, which is described as

$$\min\theta\ \ (s.t.\ \sum_{j=1}^{n}\eta_j x_{ij}+s^{-}=\theta x_0, i=1,2,\ldots,\ m$$

$$\sum_{j=1}^{n}\eta_j o_{rj}-s^{+}=o_{rj_o}, r=1,2,\ldots,\ s$$

$$\sum_{j=1}^{n}\eta_j=1$$

$$s^{-},\ s^{+},\ \eta_j\geq 0,\ j=1,2,\ \ldots,\ n) \qquad (2)$$

where

$o_{rj}=\dfrac{y_{rj}}{\delta_j}, r=1,2,\ldots s$ is the adjusted total outputs;

y_{rj} is the j^{th} DMU's r^{th} desired outputs;

$\delta_j=\sum_{l=1}^{t}\rho_l y_{lj}^{b}$ is the j^{th} DMU's total loss;

y_{lj}^{b} is the j^{th} DMU's l^{th} undesired outputs; and

ρ_l is the manual assigned weight of the l^{th} undesired outputs [11].

The proportional DEA model is superior to the original in that the former addresses the relationships between the different kinds of undesirable outputs, leading to a more reasonable evaluation of environmental efficiency [12]. However, due to a lack of constraint condition in the undesirable outputs, an ecologically sound area's undesirable outputs, as estimated by the proportional DEA model, may be higher than that of an acutely polluted area. We avoid such undesired results by adding one constraint condition—environmental capacity—to the current proportional DEA model.

Environmental capacity is a property that demonstrates the local environment's maximal pollution load without unacceptable impact. Therefore, it is central to the promotion of sustainable development. This is determined by factors like natural geographical features, the contaminants' chemical and physical properties, distribution of urban space, and pollutant transmission patterns. Consequently, the environmental capacities of different cities, and seasonal environmental capacity within a city, may differ according to the integrated standards of air pollutants and wastewater [13,14]. Currently, environmental capacity cannot be ignored when evaluating DMUs' environmental efficiency.

First, we provide the dual form of You and Yan's proportional model [11]:

$$\pi_o^{s}=\max\sum_{r=1}^{s}\mu_r O_{ro}$$

$$s.t.\frac{\sum_{r=1}^{s}\mu_r O_{rj}}{\sum_{i=1}^{m}\omega_i\chi_{ij}}\leq 1 \qquad j=1,\ldots n \qquad (3)$$

where the undesirable outputs y_{lj}^{b}, or the contaminant discharge amount, is used to characterise the undesirable outputs' environmental influence in the new model. Regarding common water and air contaminants, equal standard pollution loading is used as a new parameter to replace y_{lj}^{b} [15,16,17]:

$$p_{lj}^{b} = y_{lj}^{b} / Co_{lj} \qquad (4)$$

$$\delta_j = \sum_{l=1}^{t} \alpha_l p_{lj}^{b} \qquad (5)$$

$$O_{rj} = y_{rj} / \delta_j \qquad (6)$$

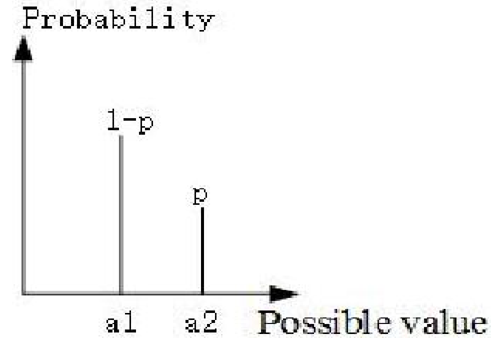
where Co_{lj} is the discharge standard (environmental capacity) of the l^th contaminant (undesirable outputs) in the area governed by the j^th decision-making unit, and α_l is the loss coefficient. Generally, all manufacturers discharge different kinds of contaminants, and the conventional DEA model assigns a weight to every kind of contaminant. However, environmental science uses the pollution load to evaluate every contaminant's influence on the environment. Therefore, this paper replaces the weighting process with the sum of the pollution loads of every contaminant.

We thus focus on the properties of Co_{lj}. First, environmental capacity, or the environment's carrying capacity, is considered to be the quantity of pollutants that can be accommodated under the specified environmental objectives. It is suggested that an ecological system's carrying capacity relates to the system's structure, which, itself, is a product of topography, meteorology, and how the region is used. A region creates a DMU if its topography remains stable with no major geological hazards, such as earthquakes. If how the region is used remains unchanged, the DMU's environmental capacity will change only with the season [18,19,20,21,22]. For example, water contaminant discharge standards for the lower region of Yangtze differ for the flooding and dry seasons. Thus, we assume two categories, for simplicity: Situation A has a small environmental capacity (dry season), and Situation B has a high environmental capacity (flooding season). The probability p is the time ratio of the flooding or dry season to the entire year.

Table 1 further defines the random variable $\hat{p}_j$.

Table 1. Distribution table of $\hat{p}_j$

Possible Value	a_1 (weight of A_1 scene)	a_2 (weight of A_2 scene)
Probability	1-p	p



Assume that the production is divided into **M** equal parts. The probability that it decreases, as in the case of A_1, is (1 – p); and the probability in the case of A_2 is p. Thus, $\hat{p}_j$ obeys the binomial distribution.

$$\hat{p}_j \sim \mathrm{B}(\mathrm{M}, p)$$

$$Co_{lj} = L_{lj}^{b} \bullet \hat{p}_j$$

$$\varphi_{lj}^{b} = \frac{\alpha_l}{L_{lj}^{b}}$$

$$\delta_j = \frac{\sum_{l=1}^{t} \varphi_{lj}^{b} y_{lj}^{b}}{\hat{p}_j} \qquad (7)$$

Based on Sueyashi, Cooper et al., and Cooper, Huang, and Li's proposed method to introduce random variables in the DEA model [23,24,25], the aforementioned formula (3) becomes

$$\pi_o^{s} = \max \sum_{r=1}^{s} \mu_r O_{ro}$$

$$s.t.\ \mathrm{pro}\left(\frac{\sum_{r=1}^{s} \mu_r O_{rj}}{\sum_{i=1}^{m} \omega_i \chi_{ij}} \le 1 \right) \ge 1\text{-}\beta_j \qquad \mathrm{j}=1,\ldots n \qquad (8)$$

where β_j is the risk attitude, representing the decision-maker's effectiveness.

Substituting the definition of the 'to' equation produces:

$$\text{pro}\left(\delta_j \geq \frac{\sum_{r=1}^{s}\mu_r y_{rj}}{\sum_{i=1}^{m}\omega_i \chi_{ij}}\right) \geq 1\text{-}\beta_j \qquad \text{j=1,}\ldots n$$

$$\text{pro}\left(\hat{p}_j \leq \frac{\sum_{i=1}^{m}\omega_i \chi_{ij} \bullet \sum_{l=1}^{t}\varphi_{lj} y_{lj}^{b}}{\sum_{r=1}^{s}\mu_r y_{rj}}\right) \geq 1\text{-}\beta_j \qquad \text{j=1,}\ldots n \qquad (9)$$

Let $Z=\frac{\sum_{r=1}^{s}\mu_r y_{rj}}{\sum_{i=1}^{m}\omega_i \chi_{ij} \bullet \sum_{l=1}^{t}\varphi_{lj} y_{lj}^{b}}$. Then, the aforementioned formula (9) becomes:

$$\text{pro}\left(Z \leq \frac{1}{\hat{p}_j}\right) \geq 1\text{-}\beta_j \qquad \text{j=1,}\ldots n \qquad (10)$$

According to the distribution function of the binomial distribution, the plan takes the following form:

$$\pi_o^s = \max \sum_{r=1}^{s}\mu_r O_{ro}$$

$$s.t. \frac{\sum_{r=1}^{s}\mu_r y_{rj}}{\sum_{i=1}^{m}\omega_i \chi_{ij} \bullet \sum_{l=1}^{t}\varphi_{lj} y_{lj}^{b}} \leq \frac{1}{\text{a}_2} \qquad \text{j=1,..} n$$

$$\text{or } \frac{\sum_{r=1}^{s}\mu_r y_{rj}}{\sum_{i=1}^{m}\omega_i \chi_{ij} \bullet \sum_{l=1}^{t}\varphi_{lj} y_{lj}^{b}} \leq \frac{1}{a_1} \qquad \text{j=1,..} n \quad \text{when p} \leq \beta_j \qquad (11)$$

Then, we convert the aforementioned formula (11) back to linear programming:

$$\min\theta \ \ (s.t. \ \sum_{j=1}^{n}\eta_j x_{ij} + s^- = \theta x_0, i = 1,2,\ldots, \text{ m}$$

$$\sum_{j=1}^{n}\eta_j o_{rj}^{a_1} - s^+ = o_{rj_0}^{a_1}, r = 1,2,\ldots, \text{ s} \quad \text{when p} \leq \beta_j$$

$$or \ \sum_{j=1}^{n}\eta_j o_{rj}^{a_2} - s^+ = o_{rj_0}^{a_2}, r = 1,2,\ldots, \text{ s} \quad \text{when others}$$

$$\sum_{j=1}^{n}\eta_j = 1$$

$$s^-, \text{s}^+, \eta_j \geq 0, \text{j=1,2,} \ \ldots, \text{ n)} \qquad (12)$$

Specifically, the evaluation should generally be done in a high-environmental capacity situation, if possible, while the manufacturer that cannot suspend its production should have a smaller environmental capacity. Further, the physics of risk attitude include the decision-maker's acceptance of the undesirable outputs. If the decision-maker cannot accept a manufacturer in a small environmental capacity, the manufacturer should operate seasonally, or the company could move to a high-environmental capacity region. This conclusion is consistent with many decisions. For example, although Beijing Shougang Co., Ltd., as well as other steel companies in Hebei Province, has high evaluation indices that use the conventional DEA model, the smog levels in Beijing and surrounding areas in the winter far surpass acceptable levels for residents. As Beijing currently shoulders too many non-capital functions, and steel companies cannot suspend their production, these companies could be the first to move into a new zone, such as Xiongan.

3. CASE STUDY

China is the world's largest textile processing country and the largest exporter of textiles in the world. According to The Ministry of Industry and Information Technology of the P.R.China (MIIT), textile processing amount of China accounts for more than 50% of the world's total amount. Although the textiles and apparels industry has a remarkable contribution to the growth of China's economy, the escalating industrial development places China's environment under pressure.In this study, China's textile industry is evaluated with DEA by taking the environmental factor into account.

As the national environmental standard system provides comprehensive water environmental capacity data, we chose textile companies located around the main stem of the Yangtze River and its tributaries: the Yuxi, Nanfei, Pai, Hangbu, and Fengle rivers. These rivers belong to four different administrative regions: Hefei, Ma'anshan, Wuhu, and Lu'an. They are located in the area around the Qinling-Huaihe line, which is a dividing line for Chinese climate, as its hydrological characteristics include the typical flooding and dry seasons.

These rivers have different environmental quality standard classifications for their surface waters, and different environmental anti-pollution abilities due to their varied functions.


Mongolia
HEILONGJIANG
Urumqi
乌鲁木齐
Almaty
INNER MONGOLIA
JILIN
XINJIANG
LIAONING
Beijing
北京
North Korea
HEBEI
Tianjin
天津
Pyongyang
평양
GANSU
NINGXIA
SHANXI
QINGHAI
SHAANXI
SHANDONG
South Korea
Yellow Sea
China
Xi'an
西安
Busan
부산
HENAN
Fukuoka
福岡
JIANGSU
The region examined
Shanghai
上海
Chengdu
成都
HUBEI
ANHUI
TIBET
SICHUAN
Chongqing
重庆
Hangzhou
杭州
East China Sea
UTTARAKHAND
ZHEJIANG
UTTAR PRADESH
Nepal
Kathmandu
SIKKIM
Bhutan
GUIZHOU
HUNAN
JIANGXI
Jaipur
Lucknow
ASSAM
BIHAR
MEGHALAYA
NAGALAND
FUJIAN
Taipei
臺北市
MANIPUR
YUNNAN
Bangladesh
TAIWAN
JHARKHAND
TRIPURA
GUANGXI
GUANGDONG
India
WEST BENGAL
MIZORAM
Kaohsiung City
Chhindwara
Macau
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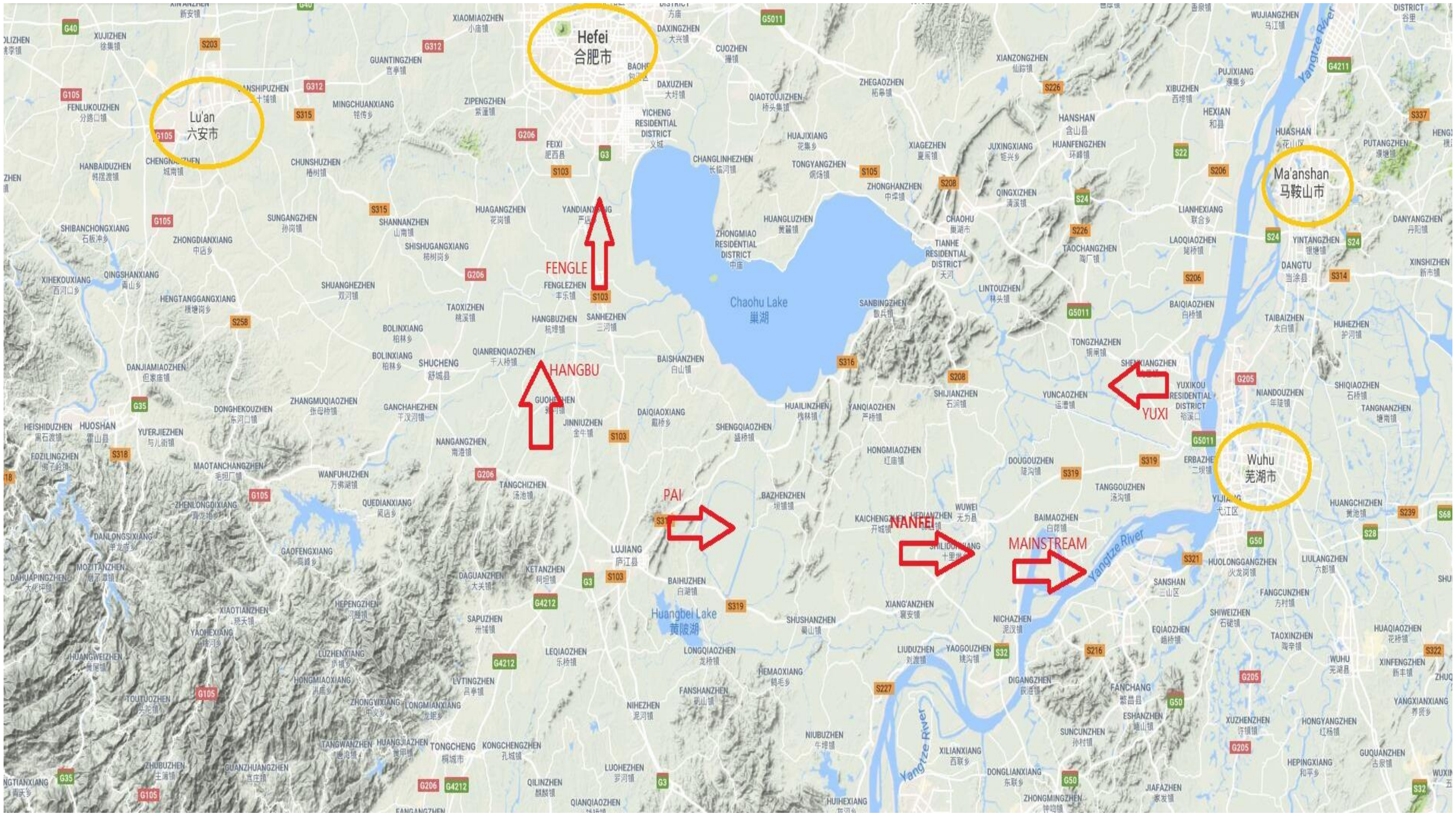

Fig. 2. The map of the region examined

According to the principles listed in the 'Water Environmental Functions in Anhui Province', the main and branch rivers of the Yangtze River cannot be smaller than Class III and Class IV, respectively [26]. These classifications are denoted according to the 'Environmental Quality Standard for Surface Water' [27], which is a national environmental protection standard. Additionally, the Hangbu and Fengle Rivers were chosen as pilot regions to implement the 'Opinion on Comprehensively Promoting the River Chief System' [28]. Therefore, this paper's calculations include the water quality from Class III in the Hefei region.

Table 2 lists the properties of the rivers noted in this paper, as well as the evaluation standards for water quality in four different administrative regions. This information is presented according to the 'Report on the Water Resource-Carrying Capacity of Anhui Province' [29], as Table 3 notes. Moreover, Table 4 lists parts of the standard values for basic environmental quality standard items for surface water according to the 'Environmental Quality Standard for Surface Water' [27].

4. DATA COLLECTION AND ANALYSIS

This paper chose the textile and clothing industry, which discharges its sewage into nearby rivers, to examine the validity of the revised DEA model according to the unpublished data from 'General Survey of Industry Pollution Sources in Anhui Province' (Department of Environmental Protection of Anhui Province, 2010) and the 'Discharge Standard for Water Pollutants of Chao Lake Basin' [30]. The primary contaminants, or the undesirable outputs, include chemical oxygen demand and ammonia. Fig. 1 summarises the inputs and outputs for the assessment. This paper differs from the original proportional DEA model in that we do not need to assign a weight for every waste water pollution factor.

Table 2. Descriptive statistics of river measurements

Watershed	River	Length (km)	Drainage area (km^2)	Flows through Cities	Water quality Standards
Yangtze	Mainstream	--	--	Wuhu/Ma'anshan	III
	Yuxi	61.7	12,938	Hefei/Ma'anshan/Wuhu	IV
	Nanfei	70	1,446	Hefei	IV
	Pai	48.9	584.6	Hefei	IV
	Hangbu	145.5	2,152	Lu'an/Hefei	IV/III
	Fengle	117	2,080	Lu'an/Hefei	IV/III

Table 3. Environmental quality targets for four cities

Cities	Target
Hefei	57%
Lu'an	85%
Ma'anshan	90%
Wuhu	92%

Table 4. Standard value of basic items for surface water environmental quality standards (units in mg/L)

Item no.	Classification Standard Value Items	Class I	Class II	Class III	Class IV	Class V
5	Chemical Oxygen Demand (COD) <=	15	15	20	30	40
7	Ammonia & Nitrogen <=	0.15	0.5	1.0	1.5	2.0

Source: 'Environmental Quality Standard for Surface Water' (Ministry of Environmental Protection of the People's Republic of China, 2002)

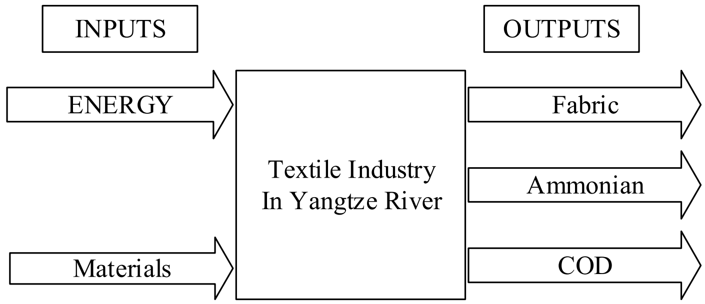

Fig. 3. The assessment's inputs and outputs

Table 5. Descriptive statistics of measures of 15 Anhui textile companies

Companies	Abbr.	Cities	Rivers	Materials used annual (million Yuan)	Energy used annual (million Yuan)	Industrial output (million Yuan)	COD (tons)	Ammonia & nitrogen (tons)
Hefei Red Cherry	CHER	Hefei	FengLe	120	4	260	14.95	2.46
Anhui Blue Sky	BLUE	Hefei	NanFei	90	3.2	200	22.65	2.25
Hefei Union Asia	UNAS	Hefei	Pai	36	1.9	70	3.60	1.60
CR Textile（Hefei）	CRTH	Hefei	Pai	200	8.5	410	1.89	0.80
Anhui Beauty Beyond	BEYO	Hefei	HangBu	70	3	135	7.19	0.16
Anhui Giant Goose	GIGO	Hefei	NanFei	95	4.2	180	8.95	3.83
Luan Green Sky	GREE	Luan	HangBu	40	2.2	90	14.45	1.4
Luan Triumphant	TRIU	Luan	FengLe	32	2	70	5.64	3.1
ChaoHu Beauty Honest	BEHO	Maanshan	YuXi	5	1.2	10	1.14	0.52
ChaoHu Lucky Clouds	LUCL	Maanshan	YuXi	13.4	1.8	21.32	10	0.03
HanShan Suncheon	SUCH	Maanshan	YuXi	9	1.6	14.5	0.19	0.09
ShuCheng Chi-Garden	CHGA	Luan	FengLe	26	9	40	21.8	0.6
Anhui Tri-Golden	TRGO	Wuhu	YuXi	9.6	10	32	0.7392	0.1056
WuHu Paul	PAUL	Wuhu	YuXi	15	7	28	0.5244	0.0828
WuWei Washing	WASH	Wuhu	Yangtze	18	6	50	1.375	0.253

We use a single seasonal factor index method to evaluate the undesirable outputs' impact on the environment due to the Yangtze River's lack of a standard seasonal discharge in Anhui Province. This method, which is commonly used in environmental science, is an alternative to using the seasonal discharge standard. Further, this method is also a robust way to consider situations in which pollution has already surpassed the standard. The dry season occurs from December to February of the following year, or approximately 25% of the year. In this case,

$$S_{lj} = \frac{C_{lj} \bullet Q + y_{lj}^{b}}{C_{s,lj}}$$

$$\delta_j = \sum_{l=1}^{t} S_{lj}$$

where $C_{s,lj}$ is the upper evaluation limit of the lth contaminant, as determined by the local water quality standard of the area of the jth DMU. Further, y_{lj}^{b} is the total amount of the lth discharged contaminants in the evaluation season, as the manufacturer is assumed to be month-independent. Q is the water fluctuation in the evaluation season when disregarding the increase of Q water flux because of discharged contaminants. Finally, the average value of the monitoring section in the evaluation season C_{lj} provides the water environment background.

5. RESULTS AND DISCUSSION

5.1 The Results from Calculating the Proportional and Improved Proportional Models

The acceptable risk attitude involves the water quality reaching the standard value. To achieve a high evaluation score, manufacturing companies in Lu'an, Ma'anshan, and Wuhu should focus on the 'flood and flat' water seasons. Manufacturing companies in Hefei operate independent of the season, and their environmental effects are estimated in the dry season. Additionally, other data corresponding to the entire manufacturing year are provided using the modified model and marks. The weighed factors of chemical oxygen demand and ammonia in the original proportional model are artificially rated as 1 and 3, respectively.

The calculation results shown in Tables 5 and 6 and Fig. 2 clearly indicate that all the textile and clothing companies have incredibly high efficiency as per the conventional DEA model. Such high efficiency comes from intense competition over many years, as well as neglect from environmental pollution. When environmental pollution is considered, such efficiency may change significantly, as quantitatively demonstrated by the proportional DEA model's results. The evaluation score for a company that focuses on expanding production capacity and ignoring environmental pollution (e.g. Hefei Red Cherry) dramatically decreases from 1.0 in the conventional DEA model to a range from 0.1 to 0.15 in the proportional model. The overall average efficiency value decreases by half, indicating that economic development is accompanied by environmental pollution.

To clearly reveal the effects of environmental capacity, the estimated results of the proportional DEA model are compared with those of the modified model. We found that the results of the two models approximate each other in most cases, with an efficiency difference of 0.01 to 0.02, and both have effective DMU scores of 1. However, note that the company in Hefei exhibits markedly different efficiencies, as estimated by the two models. As an economic centre, Hefei must carry the highest population and economic actions, resulting in acute environmental problems. This difference indicates that the environmental capacity approaches its upper limit in an acutely polluted region, and the undesirable outputs' impact dramatically increases in the modified proportional DEA model. For example, the production efficiencies of Anhui Blue Sky and Hefei Union Asia further decrease to 0.04, and the decreased magnitude of Hefei Union Asia's production efficiency is approximately 50%. This is because these companies discharge contaminants into the

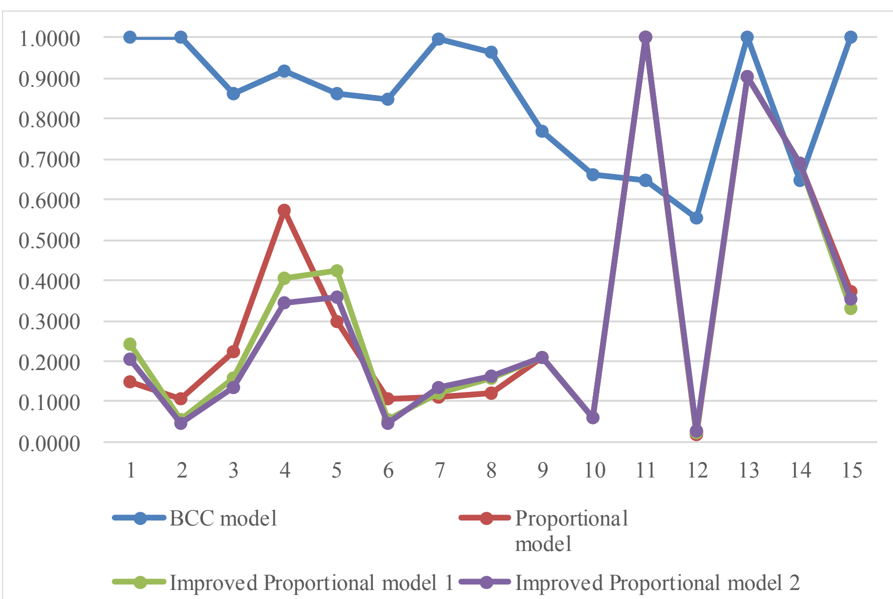

Fig. 4. Overall efficiencies under the BCC/proportional and improved proportional models

Table 6. Overall efficiencies under the BCC/proportional and improved proportional models

No.	Companies	Efficiency score			
		BCC model	Proportional model	Improved proportional model 1	Improved proportional model 2
1	Hefei Red Cherry	1.0000	0.1478	0.2425	0.2046
2	Anhui Blue Sky	1.0000	0.1079	0.0575	0.0486
3	Hefei Union Asia	0.8625	0.2226	0.1583	0.1336
4	CR Textile（Hefei）	0.9172	0.5707	0.4058	0.3424
5	Anhui Beauty Beyond	0.8626	0.2978	0.4235	0.3574
6	Anhui Giant Goose	0.8465	0.1064	0.0568	0.0479
7	Luan Green Sky	0.9962	0.1113	0.1188	0.1336
8	Luan Triumphant	0.9626	0.1189	0.1585	0.1646
9	ChaoHu Beauty Honest	0.7682	0.2115	0.2115	0.2115
10	ChaoHu Lucky Clouds	0.6611	0.0596	0.0596	0.0596
11	HanShan Suncheon	0.6477	1.0000	1.0000	1.0000
12	ShuCheng Chi-Garden	0.5518	0.0186	0.0248	0.0258
13	Anhui Tri-Golden	1.0000	0.9013	0.9013	0.9013
14	WuHu Paul	0.6476	0.6897	0.6897	0.6897
15	WuWei Washing	1.0000	0.3717	0.3304	0.3521
	Mean	0.8483	0.3290	0.3226	0.3115
	Numbers of efficient DMU	4	1	1	1

Table 7. Overall ranking under the BCC/proportional and improved proportional models

No.	Companies	Rank			
		BCC model	Proportional model	Improved proportional model 1	Improved proportional model 2
1	Hefei Red Cherry	1	9	7	8
2	Anhui Blue Sky	1	12	13	13
3	Hefei Union Asia	9	7	10	11
4	CR Textile（Hefei）	7	4	5	6
5	Anhui Beauty Beyond	8	6	4	4
6	Anhui Giant Goose	10	13	14	14
7	Luan Green Sky	5	11	11	10
8	Luan Triumphant	6	10	9	9
9	ChaoHu Beauty Honest	11	8	8	7
10	ChaoHu Lucky Clouds	12	14	12	12
11	HanShan Suncheon	13	1	1	1
12	ShuCheng Chi-Garden	15	15	15	15
13	Anhui Tri-Golden	1	2	2	2
14	WuHu Paul	14	3	3	3
15	WuWei Washing	1	5	6	5

Nanfei and Pai Rivers, which are severely polluted. In contrast, Hongyingtao’s production efficiency has increased because it discharges contaminants into the Fengle and Hangbu Rivers, which have excellent water quality. The efficiency difference between the proportional and modified DEA models decreases with the increase in environmental capacity and the decrease in the magnitude of environmental pollution. This amplification effect in the modified model especially adapts the modified DEA model for regions with prominent environmental problems. The precision of the conventional proportional model is sufficient for slightly polluted or ecologically excellent regions.

5.2 Discussion

In the modified Model 1, we assume that the risk attitude requirements for all regions, except

Hefei, are high, and the production in these regions is seasonal. Although pollution emissions are concentrated, and the total emissions remain constant, the large environmental capacity makes these companies' efficiency the same as that in Model 2. Simultaneously, the efficiency of companies in Hefei City, as indicated by the modified Model 1, is higher than those in the modified Model 2, in which the companies in all four regions have the same, low risk attitude. Consequently, the efficiencies of all companies in Hefei City again decrease, comparatively speaking. Clearly, this is why such polluting enterprises should be transitioned from developed, but acutely polluted, regions to developing, yet uncontaminated, regions. The DMUs anticipated environmental efficiency appropriately decreases in the developing region, but not environmental quality, as the original environmental goal should remain unchanged. This achieves relatively low production efficiency in the original region, and optimises the industrial spatial pattern.

6. POLICY IMPLICATIONS

Based on the study's results, we provide the following policy implications for the Chinese government.

1. Environmental efficiency is a vital index to evaluate performance of ecological conservation, as it can truly reveal the concrete relationships between different regions' inputs and outputs during production processes with undesirable outputs.
2. The industrial spatial pattern optimisation policy can be used to improve regional environmental efficiency. High-polluting companies should transition from developed, low-environmental capacity regions to developing, high-environmental capacity regions. For example, Xiongan's new area, established by the Chinese government, will help restructure the industrial layout in the Beijing–Tianjin–Hebei region, and relieve environmental pressure.
3. Environmental capacity and the acceptance of pollution should be comprehensively considered when the transformed industry moves to developing regions, as basic functional planning must be ensured. Further, it should be noted that, it is inadvisable to trade the environment for economic benefits.
4. Different industrial policies and performance evaluation criteria will be applied to different regions based on their functional zoning. Developed regions can anticipate increased environmental efficiency; a strict industrial access system is also necessary. However, the anticipated environmental efficiency and industrial access standards for the developing region can be marginally decreased to promote economic development.
5. The River Chief System and Regional Cooperation Mechanism should be established in the Yangtze River Delta to improve national environmental efficiency. This will help consider environmental capacity and risk attitudes. Only in this way can we achieve lasting and sustainable development in China.

7. CONCLUSIONS

The DEA method has been widely applied to evaluate environmental efficiency. However, few studies address the effects of undesirable outputs by evaluating the performance of ecological conservation. This paper primarily aims to introduce a modified proportional DEA model that uses uncertain factors, such as environmental capacity and endowed risk attitude with practical meanings, to constrain undesirable outputs. The modified model calculates the environmental efficiency of textile and clothing companies located around the main stem and tributaries of the Yangtze River during the 12th Five-Year Plan. The empirical results demonstrate that the modified proportional DEA model is more suitable than the conventional proportional DEA model to evaluate the environmental efficiency of companies in acutely polluted regions—the more prominent the environmental pollution, the more suitable the modified model.

Our empirical study, which used the modified proportional DEA model, revealed that (1) environmental efficiency is approximately proportional to environmental capacity, and low environmental capacity corresponds to low environmental efficiency; (2) generally, for the same environmental capacity, higher acceptance of risk attitude results in lower environmental efficiency; and (3) different regions have different risk attitudes, and the anticipation of environmental efficiencies could be adjusted according to the actual situation.

COMPETING INTERESTS

Authors have declared that no competing interests exist.

REFERENCES

1. Ministry of Environmental Protection of the People's Republic of China. Report on the State of the Environment in China. 2016;7-16.
2. Hendrik A, Bidwell VR. Measuring eco-efficiency: A guide to reporting company performance. World Business Council for Sustainable Development. 2000;36.
3. Hua Z, Bian Y. DEA with undesirable factors. In J. Zhu & W. D. Cook (Eds.), Modeling data irregularities and structural complexities in data envelopment analysis. Boston: Springer Science. 2007;103–121.
4. Berg SA, Forsund FR, Jansen ES. Malmquist indices of productivity growth during the deregulation of Norwegian banking 1980–1989. Scandinavian Journal of Economics. 1992;94(0):211–28. Supplement.
5. Hailu A, Veeman T. Non-parametric productivity analysis with undesirable outputs: an application to Canadian pulp and paper industry. American Journal of Agricultural Economics. 2001;83(3):605–16.
6. Seiford LM, Zhu J. Modeling undesirable factors in efficiency evaluation. European Journal of Operational Research. 2002; 142(1):16–20.
7. Hua Z, Bian Y, Liang L. Eco-efficiency analysis of paper mills along the Huai River: An extended DEA approach. Omega. 2007;35:578–587.
8. Chung Y, Färe R, Grosskopf S. Productivity and undesirable outputs: A directional distance function approach. Journal of Environmental Management. 1997;51(3): 229–40.
9. Charnes A, Cooper WW, Rhodes E. Measuring the efficiency of decision making units. European Journal of Operational Research. 1978;2:429–444.
10. Banker RD, Charnes A, Cooper WW. Some models for estimating technical and scale inefficiencies in data envelopment analysis. Management Science. 1984;30: 1078–1092.
11. You S, Yan H. A new approach in modeling undesirable outputs in DEA model. Journal of the Operational Research Society. 2011; 62:2146–2156.
12. Lu W, Zhao Y. Chinese regional environmental efficiency rating and its influence factors. Journal of Beijing University of Aeronautics and Astronautics (Social Sciences Edition). 2016;29(3):4.
13. Ministry of Environmental Protection of the People's Republic of China. Integrated Emissions Standard of Air Pollutants (GB16297-1996); 1996.
14. Ministry of Environmental Protection of the People's Republic of China. Integrated Wastewater Discharge Standard (GB8978-1996); 1996.
15. Hong Y, Liu F, Dou Y, Zou H. Method of pollution sources assessment in relation to residential site selection. Journal of Cleaner Production. 1998;6(3–4):357–363.
16. Rodríguez A, Rosall R, Perdigón-Melón JA, Mezcua M, Agüera A, Hernando MD, Letón P, Fernández-Alba AR, García-Calvo E. Ozone-based technologies in water and wastewater treatment. Handbook of Environmental Chemistry. 2008;5S/2(5): 127–175.
17. Zhong DS, Zhang HW. Equal standard pollution load method for evaluating the effect of pollution source on aquatic environment. China Water & Wastewater. 2005;21(5):101–103.
18. Wu Y, Chen J. Investigating the effects of point source and nonpoint source pollution on the water quality of the East River (Dongjiang) in South China. Ecological Indicators. 2013;32(32):294–304.
19. Yan MI, Chang SL, Shi QD, Gao X, Huang C. Study on the effect of agricultural nonpoint source pollution to water environment of the Ebinur Lake basin during high flow period. Arid Zone Research. 2010;27(2):278–282.
20. Xing G, CaoShulian Y, SunLijuan S, Zhu D. N pollution sources and denitrification in waterbodies in Taihu Lake region. Science China Chemistry. 2001;44(3):304–314.
21. Zhang YL, Hong JH, Xia Q. Prospect and progress on water environment capacity research in China. Research of Environmental Science. 1988;1(1):73–81.
22. Yapp GA. The nature and carrying capacity of recreation environment Doctoral dissertation (12503137), Libraries Australia, Canberra, Australia; 1978.
23. Sueyoshi T. Stochastic DEA for restructure strategy: An application to a Japanese

petroleum company. Omega. 2000;28(4): 385–398.

24. Cooper WW, Deng H, Huang ZM, Li SX. Chance constrained programming approaches to technical efficiencies and inefficiencies in stochastic data envelopment analysis. Journal of the Operational Research Society. 2002; 53(12):1347–1356.
25. Cooper WW, Huang Z, Li S. Satisficing DEA models under chance constraints. Annals of Operations Research. 1996; 66(4):279–295.
26. Department of Water Resources of Anhui Province. Water Functional Zones of Anhui Province. 2003;62–88.
27. Ministry of Environmental Protection of the People's Republic of China Environmental Quality Standard for Surface Water (GB 3838-2002); 2002.
28. General Office of the State Council of the People's Republic of China. Opinion on Comprehensively Promoting the River Chief System; 2003.
29. Department of Water Resources of Anhui Province. Report on Water Resource-Carrying Capacity of Anhui Province. 2017; 46–62.
30. Department of Environmental Protection of Anhui Province. Discharge Standard for Water Pollutants of Chao Lake Basin (DB34/2710-2016); 2016.

APPENDIX

Companies involved in the study

Companies	Abbr.	Cities	Rivers
Hefei Red Cherry Textile Co., Ltd.	CHER	Hefei	Fengle
Anhui Blue Sky Towel Co., Ltd.	BLUE	Hefei	Nanfei
Hefei Union Asia Clothing Co., Ltd.	UNAS	Hefei	Pai
CR Textile (Hefei) Co., Ltd.	CRTH	Hefei	Pai
Anhui Beauty Beyond Textile Co., Ltd.	BEYO	Hefei	Hangbu
Anhui Giant Goose Textile Co., Ltd.	GIGO	Hefei	Nanfei
Lu'an Green Sky Home Textile Co., Ltd.	GREE	Lu'an	Hangbu
Lu'an Triumphant Knitted Garment Co., Ltd.	TRIU	Lu'an	Fengle
ChaoHu Beauty Honest Textile Co., Ltd.	BEHO	Ma'anshan	Yuxi
ChaoHu Lucky Clouds Textile Co., Ltd.	LUCL	Ma'anshan	Yuxi
HanShan Suncheon Textile Co., Ltd.	SUCH	Ma'anshan	Yuxi
ShuCheng Chi-Garden Clothing Co., Ltd.	CHGA	Lu'an	Fengle
Anhui Tri-Golden Textile Co., Ltd.	TRGO	Wuhu	Yuxi
WuHu Paul Textile Co., Ltd.	PAUL	Wuhu	Yuxi
WuWei Washing Textile Co., Ltd.	WASH	Wuhu	Yangtze

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