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Energy Poverty Impact on Sustainable Development of Water Resources in China: The Study of an Entropy Recycling Dynamic Two-Stage SBM Model

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Abstract: Water scarcity is increasingly being recognized as a global concern. Sustainable Development Goal 6 (SDG-6) was established by the United Nations to address water resource governance within its sustainable development framework. This study employs the entropy weight method and a two-stage cyclical dynamic slacks-based measure (SBM) model to scientifically evaluate water resource utilization and governance across various regions in China. The findings reveal notable disparities in both the production and governance efficiency of water resources. Recognizing governance efficiency is crucial for promoting sustainable water resource utilization and socioeconomic development. The eastern, central, and western regions encounter unique challenges in attaining sustainability. The eastern region exhibits minimal potential for enhancing technical efficiency, necessitating interventions in management strategies and resource allocation. Conversely, the challenges in the central and western regions are more pronounced, demanding immediate implementation of new technologies and equipment. The data analysis in this study yields conclusions that offer targeted improvement recommendations to address disparities across China's eastern, central, and western regions, and this is achieved by considering various developmental stages and regional contexts. These recommendations cover areas such as technical support, financial investment, and policy incentives, with the aim of enhancing the sustainable utilization of water resources in the country.

Keywords: entropy method; SBM-DEA; SDG-6; sustainable; water resources

Citation: Li, Y.; Du, L.; Chiu, Y.-H. Energy Poverty Impact on Sustainable Development of Water Resources in China: The Study of an Entropy Recycling Dynamic Two-Stage SBM Model. *Water* **2024**, *16*, 876. https://doi.org/10.3390/w16060876

Academic Editor: Renato Morbidelli

Received: 29 January 2024
Revised: 4 March 2024
Accepted: 11 March 2024
Published: 18 March 2024

1. Introduction

The scarcity of water resources has become a grave concern shared by all of humanity. Simultaneously, with the growth of the population and the acceleration of urbanization, it is anticipated that water resource shortages will continue to worsen over the next several decades. Furthermore, natural factors and human activities have severely disrupted the water cycle process. This leads to an unstable water supply [1] and imbalances in water resource provisioning. The accurate assessment of water resource sustainability is fundamental to mitigating human–water conflicts [2]. The sixth United Nations' Sustainable Development Goal is dedicated to 'ensuring availability and sustainable management of water and sanitation for all', with the expectation of achieving the requirements outlined in SDG-6 by 2030 [3]. However, China, as the second-largest water consumer in the world [4], is among the thirteen countries with the lowest urban water resource utilization efficiencies and is facing severe water resource challenges [5]. The critical lack of water resources has become one of the primary bottlenecks for urban, economic, and social sustainable development [6].

Water and energy are two critical natural resources essential for human activities and socioeconomic development, and water efficiency and energy efficiency are two related indicators of the United Nations' Sustainable Development Goals [7]. Among these, energy poverty is a typical form of poverty and a hot topic globally related to sustainable energy development. Scholars have various definitions for energy poverty, with the International Energy Agency (IEA) [8] proposing a definition that is more suitable for developing countries, i.e., one that involves a lack of access to electricity, clean fuels, and energy facilities, as well as a high dependence on traditional fuels. In recent years, the socioeconomic and environmental impacts of assessing energy poverty have become a widely recognized topic in this field [9].

In existing research, scholars have employed various methods to measure the efficiency of water resource sustainability. In studies that have investigated the efficiency scores for water resource sustainability, the application of data envelopment analysis methods (DEAs) has been widespread. They have been used to investigate regional heterogeneity in water resource governance, relevant input–output variables, and strategies through which to enhance the sustainability of water resource utilization [10–12]. Certain research has also assessed the drivers of SDG-6 in low- and middle-income countries worldwide [13]. Additionally, panel data studies have constituted a portion of the research, which has focused on exploring the contributions of different factors to their study variables and overall trends in change [7].

Meanwhile, certain studies have noted that China's vast territory is characterized by economic disparities among different regions, thus leading to inefficiencies in resource allocation. China's hydropower resources are spatially distributed in a highly uneven manner, with water resources concentrated mainly in the southeastern regions. In contrast, energy resources are predominantly located in the central and northern areas [14]. This mismatch in energy distribution and efficiency issues in other resource allocations hinder the integrated utilization of water and energy resources [15].

Based on the above-mentioned research, we have identified certain inherent limitations in previous studies, including the need to improve the methods and models employed as well as ameliorate the limitations from a research perspective. Firstly, in studies discussing urban water resource utilization efficiency, most of the research has focused on the green use of water resources in the industrial and agricultural sectors, with relatively fewer studies on regional water resource comprehensive efficiency [16]. Furthermore, certain scholars have suggested that, for more effective regional research, it is necessary to conduct studies that compare the production efficiency and technological disparities in different regions under the same benchmark [17].

In light of the limitations observed in existing research, this study makes significant advancements in the following areas:

To integrate these complex output indicators and to achieve a more comprehensive efficiency assessment, we utilized the entropy weight method to calculate the two-stage output variables and link variables.

Water and energy are critical natural resources for human activities and socioeconomic development. There are significant variations in resource endowments across different regions in China. In the model construction, we introduced the exogenous variable 'energy poverty' to explore its impact on efficiency assessment.

This study assesses water resource utilization efficiency by employing suitable models and methodologies. It identifies stage-specific issues by analyzing the efficiency scores of stages and components, thereby establishing improvement priorities that target critical factors influencing overall efficiency. Drawing from issue identification and regional analyses, this study proposes precise policy recommendations and measures.

This paper is divided into six main sections: the first section is the Introduction; the second section provides a review and critique of the existing research; the third section explains the methodology, model construction, and data description; the fourth section conducts an in-depth data analysis, wherein the efficiency scores obtained through model construction are analyzed, and the technical efficiency and its variations in the eastern, central, and western regions are also discussed; the fifth section presents the conclusions;

the sixth section provides policy recommendations; and the final section is on the research limitations and prospects.

2. Literature Review

In this section, we review the literature that was conducted on sustainable water resource utilization and efficiency assessments. We screened the field of study and obtained approximately a thousand relevant references. The primary focus of this review was on the literature from the past five years, as well as on summarizing the recent research trends and the methods employed in the field during this period.

2.1. Research Direction of the Sustainable Utilization of Water Resources

To accurately assess the sustainability of water resources, scholars have combined three indicators: the Water Resource Fairness Index, the Water Resource Efficiency Index, and the Water Resource Ecological Security Index. These were outlined to form a Water Resource Sustainability Index. They have used this index to diagnose the spatial characteristics of water resource sustainability in various provinces and municipalities in China, and they have found that low water resource utilization efficiency is a key factor constraining its sustainability [2]. Furthermore, based on Sustainable Development Goal 6 proposed by the United Nations, research has also improved the indicator formulas by relying on documents passed by the United Nations to ensure that more countries can access these data [18].

While exploring measurement indicators, scholars have also investigated factors influencing environmental sustainability efficiency. Studies like Ding et al. [19] have examined the impact of economic development level, industrial and agricultural structure, water resource abundance, and government intervention on regional differences in water resource utilization. Additionally, macrofactors such as technological progress and industrial structure are considered to impact water resource utilization efficiency [14]. Additionally, there has been research from an economic perspective that has examined the influence of financial agglomeration on green water resource efficiency. In this research, an inverted U-shaped relationship between financial agglomeration and green water resource efficiency has been discovered, with significant regional disparities in the effect of financial agglomeration on water resource utilization efficiency [20].

These frameworks for measuring water resource sustainability provide a possibility for standardized procedures, thereby contributing to multi-level governance and cooperation in the field, particularly in terms of emphasizing the enhancement of support for developing countries [21]. Conversely, certain scholars have argued that water governance models should incorporate collaboration, coordination, and stakeholder participation to more effectively address sustainability challenges [22]. Translating theoretical insights into practical applications and targeting the strengthening of water resource management is crucial. Previous research has suggested that enhancing coordination between jurisdictions and departments, as well as establishing mechanisms for cooperation and communication, can promote multi-level cooperation among the various sectors on water resource issues [23].

Regional disparities exist in resource endowment and economic and social development levels among China's provinces, municipalities, and autonomous regions. In studies analyzing governance efficiency, regional heterogeneity must be considered. Sun and Ma [24] identified the characteristics of the spatial correlation network of China's water resource green efficiency. The eastern regions are leading in this respect, as they are dominated by spillover effects, while the central and western regions occupy peripheral positions within the network structure.

Analyzing water resource utilization efficiency at the city level is vital for promoting urban sustainability. Certain scholars have examined issues related to water resource utilization efficiency, wastewater treatment efficiency, water resource utilization planning, regional optimization allocation, and disparities in efficiency averages, as well as in spatial distribution based on China's regional divisions [11,23,25–27]. Furthermore, the existing research has focused on improving overall regional water use efficiency by optimizing water usage structures and spatial layouts [28]. However, most of these studies have primarily provided descriptive statistics on regional differences; thus, more dynamic modeling and differentiated numerical representations over time are needed.

As it is different from idealized research modeling, defining a single governance model is impossible. Sustainable development is a vital area where the objectives of energy and water intersect, and some of the scholars researching SDG-6 have also analyzed the relationship between water and energy, as well as the connections with the other Sustainable Development Goals [29]. Wang et al.'s study estimated the water–energy coupling efficiency in different regions of China using a three-stage SBM-DEA model with panel data from 30 provinces and municipalities [14].

Simultaneously, certain researchers have argued that the degree of energy poverty is correlated with economic levels; thus, studies that have only explored the relationship between energy poverty and the other Sustainable Development Goals need further refinement [9]. The connections between energy poverty and various policy areas that influence energy poverty have yet to be sufficiently researched [30].The relevant summary of this part is shown in Table 1.

Table 1. Summary of the existing research topics.

Research Directions	Subdivision Topics	Related Scholars
Construction of index system to measure the sustainable development of water resources	Water Resource Sustainability Index	Li et al., 2022 [2]
	Sustainable Development Goals	Cai et al., 2021 [18]
Factors affecting environmental sustainability efficiency	Economic and financial factors	Ding et al., 2018 [19] Wang et al., 2019 [14] Zhang et al., 2021 [20]
	Policy and industrial structure	
	Technical level	
Spatial dimension and resource endowments	Regional heterogeneity	Song et al., 2022 [11] Fu et al., 2020 [25] Yang et al., 2020 [23] Liang et al., 2023 [26]
Urban differentiation and related policies	Sustainable development of cities	Messerli et al., 2019 [21] Di Vaiort et al., 2021 [22] Yang et al., 2020 [23]
	Standardization management and multi-level cooperation	

2.2. Research Methods for the Sustainable Utilization of Water Resources

To analyze water resource utilization efficiency over time and across spatial dimensions, certain studies have utilized polynomial regression models to analyze the changes and trends in water and energy efficiency over the period covered by the panel data [7]. Issues related to water resources and economic growth have also attracted scholarly attention. Hao et al. [31] conducted related research in the context of China using the Environmental Kuznets Curve. This method focuses on exploring trends, calculating the correlations of factors, and assessing their contributions to outcomes.

The entropy method is a comprehensive approach that integrates multiple indicators by representing different allocation principles, thereby allowing for a more rational allocation of results. This method overcomes the limitations of a single indicator by determining the dispersion level of each indicator, and indicators with higher dispersion should be assigned higher weights. The process of water resource utilization and governance is complex. Under the framework of the United Nations' SDG-6, different scholars have selected a rich set of indicators to calculate the efficiency of this process. To scientifically couple these complex indicators, the entropy method has become a commonly used approach to determining indicator weights, thus achieving comprehensive evaluation [32]. Du et al. [33] combined the entropy method with the fuzzy linguistic judgment method to derive weights for various indicators.

The methods for input–output efficiency evaluation are primarily categorized into parametric and non-parametric methods. Among the parametric methods, stochastic frontier analysis (SFA) is the most commonly used approach. However, this method needs help in addressing problems involving multiple outputs [34]. Therefore, data envelopment analysis (DEA), as a non-parametric method, has become the mainstream approach in recent years.

The classical models of DEA also have certain limitations. For example, the BCC model lacks the property of unit invariance, and improvements in both radial and non-radial aspects can lead to information loss [35]. To address the deficiencies of existing models, the SBM (slacks-based measure) model was introduced to provide a more accurate measurement of efficiency. The SBM model estimates efficiency using non-radial and non-oriented approaches, as well as by considering both input and output slacks. Furthermore, its estimated efficiency values fall between 0 and 1. When the efficiency value of a decision-making unit (DMU) is equal to 1, it signifies that the unit operates on the production frontier with no slack in inputs and outputs. This method allows for the adjustment of inputs and outputs in unequal proportions, and it avoids assuming the radial growth of undesirable outputs [36].

Yang et al. used the SBM-DEA model under constant returns to scale (CRS-SBM-DEA) technology to find solutions [23]. Guo et al. employed the SBM–Tobit model and took Henan Province in China as an example through which to calculate and analyze the internal urban water resource sustainable utilization efficiency, as well as to investigate the operating mechanism of related influencing factors [16]. Similarly, Liang et al. evaluated water resource utilization efficiency in 14 cities within Gansu Province using the SBM-undesirable model and analyzed the regional efficiency differences and trends [26]. This study also used the Dagum Gini coefficient to measure regional disparities. Zhang et al. combined DEA and AHP methods to explore the efficiency of residential and industrial agricultural water use, thereby highlighting the importance of technical efficiency in influencing water use efficiency [37].

Traditional DEA models can only measure static efficiency to some extent and cannot facilitate dynamic comparisons. Under this static framework, the heterogeneity of water use technology among Chinese provinces (cities and autonomous regions) has yet to be fully considered [38]. To provide a more realistic reflection of the efficiency issues in the input–output process, multistage DEA models that focus on dynamic processes are becoming increasingly popular. Static DEA models overlook the temporal inter-correlation between subsequent time points, while dynamic DEA and network DEA approaches are based on the concepts of “multi-period production” and “multistage production”, respectively [39].

Yang used a data envelopment analysis–Tobit (DEA–Tobit) two-stage model to assess water resource utilization efficiency, analyze regional differences in water resource utilization and influencing factors, and investigate the relationship between various types of water use and industrial structure with water resource utilization efficiency [40]. Liang et al. [41] proposed an improved two-stage network DEA model that determined the weights for each stage from both the weight and solution method aspects under the VRS assumption. They divided the overall water resource sustainability process into water resource utilization and wastewater treatment parts. Bronner et al. (2022) introduced a dynamic network DEA model and used it to assess the water economic and technical efficiency of the German federal states. A study evaluating the efficiency and spatio-temporal differences in water resource utilization in Chinese cities employed a two-stage DEA model combined with spatial econometrics. This helped to improve the traditional DEA model using Shannon entropy [42].

In summary, the existing research on sustainable water resource utilization primarily focuses on establishing standardized frameworks for environmental sustainability indicators and exploring related factors. These studies delved into water resource utilization; multi-level cooperation; efficiency score calculations at the national, regional, and city levels; temporal trend analysis; and differential examinations based on regional analyses.

The main methods used include regression models to investigate impact contributions and trend changes; stochastic frontier analysis (SFA), which considers multiple input–output factors; and data envelopment analysis (DEA). Scholars have conducted various model explorations based on the specific needs of their research designs within these frameworks.

However, most of these evaluations of water resource sustainability benefits focus on overall water resource green efficiency, thus neglecting the internal structure and mechanisms of complex systems. In response to the research background and limitations of the existing studies described earlier, this study—in conjunction with the United Nations' Sustainable Development Goal SDG-6—has constructed a comprehensive input–output indicator system intending to provide more practical macro-level recommendations. Additionally, to better integrate multiple indicators, the entropy weighting method was employed to calculate the output indicators in a two-stage process. Subsequently, a dynamic, two-stage SBM-DEA model that accounts for exogenous variables like energy poverty was developed. This study examines the water resource green efficiency scores in different regions and stages, as well as the regional technical efficiency differences under various frontier frameworks.

3. Model and Methodology

3.1. Methodology

In 2001, Tone introduced the slacks-based measure (SBM) model, which utilizes slack variables to gauge efficiency [43]. The SBM model considers the gaps (slack) between input and output variables, and it employs a non-radial estimation method to express efficiency as a scalar value. In contrast to traditional DEA methods, the SBM model not only assesses the efficiency of production units but also incorporates slack resources within their production processes. This enables evaluators to account for instances of underutilized resources, thus leading to a more comprehensive assessment of operational status and facilitating the formulation of more effective improvement strategies.

Tone and Tsutsui subsequently proposed the weighted slacks-based measure (WSBM) network data envelopment analysis (DEA) model [44]. This model utilizes inter-departmental connectivity within decision-making units as the analytical basis for the network DEA model. Each department is considered a sub-decision-making unit (Sub-DMU), and the SBM model is then utilized to determine the optimal solution. In 2014, Tone and Tsutsui proposed the WSBM dynamic network DEA model [45]. This model utilizes the inter-connectivity (linkage) between various departments within decision-making units as the analytical foundation for the network DEA model. Each department is treated as a Sub-DMU, and carryover activities spanning multiple periods are considered linkages. However, the dynamic network DEA model introduced by Tone and Tsutsui [45] did not take into account issues related to exogenous variables, regional disparities, the circular economy, and the challenge of dealing with an excessive number of variables. To address the aforementioned issues, this study integrates the entropy method proposed by Shannon (1948), the dynamic network DEA model employed by Tone and Tsutsui [45], and the circular economy framework mentioned in Sun et al. [46]. Additionally, exogenous factors are also incorporated.

The entropy method will be introduced first, followed by the meta entropy dynamic two-stage SBM recycling method under an exogenous variable DEA model.

3.1.1. The Entropy Method

In this model, both the first-stage and second-stage output variables encompass numerous sub-indicators. Introducing these detailed sub-indicators directly into the DEA model would result in an intractable problem. Therefore, this model initially employs the Shannon (1948) entropy method to compute a consolidated value for the first-stage desirable outputs as follows: (1) per capita water consumption, (2) total agricultural water usage, and (3) total industrial water usage; and for the second-stage desirable outputs as follows: (1) per capita wastewater improvement, (2) per capita CDC (chemical oxygen demand) improvement, and (3) per capita ammonia improvement output. The undesirable outputs in the first stage are also calculated using the same entropy weighting method to obtain indices such as the wastewater index and gas index.

Step One: Data standardization.

Calculate the first-stage output factors and undesirable outputs for the aforementioned 29 provinces and cities using the following formulas:

$$r_{mn} = \frac{\max\limits_{m} x_{mn} - x_{mn}}{\max\limits_{m} x_{mn} - \min\limits_{m} x_{mn}} \ (m = 1, \ldots, 29;\ n = 1, \ldots, N) \tag{1}$$

where r_{mn} is the standardized value of the nth indicator for the m_{th} province or city; $\underset{m}{min} x_{mn}$ is the minimum value of the nth indicator for the m_{th} province or city; and $\underset{m}{max} x_{mn}$ is the maximum value of the nth indicator for the mth province or city.

Step Two: Sum the standardized values calculated in Step One.

$$P_{mn} = \frac{R_{mn}}{\sum_{m=1}^{29} R_{mn}} \ (m = 1, \ldots, 29;\ n = 1, \ldots, N) \tag{2}$$

where P_{mn} represents the sum of standardized values for the n_{th} indicator across the m provinces or cities.

Step Three: Calculate the entropy value for the nth indicator $(\mathrm{e_n})$.

$$e_n = -(\ln 29)^{-1} \sum_{m=1}^{29} [P_{mn} \ln(P_{mn})] \ \ (m = 1, \ldots, 29;\ n = 1, \ldots, N) \tag{3}$$

Step Four: Calculate the weight for the nth indicator (w_n).

$$w_n = \frac{1 - e_n}{\sum_{n=1}^{N} (1 - e_n)} \ (n = 1, \ldots, N) \tag{4}$$

Using the above steps, determine the weights and output values for the first-stage and second-stage outputs. According to the aforementioned entropy method, the following meta entropy dynamic two-stage SBM recycling method under an exogenous variable DEA model is introduced, and its description is as follows.

3.1.2. Meta Entropy, Dynamic, Two-Stage SBM Recycling Method under an Exogenous Variable DEA Model

Assume there are n decision-making units (DMUs) (n = 1, . . ., n), k stages (k = 1, . . ., K), and T periods of time (t = 1, . . ., T). Each DMU then has its own set of input and output variables for each period t, and these variables are interconnected through carryover to the next period, t + 1.

Let m_k and r_k represent the input and output variables in each stage k, and let $(\mathrm{k}, h)_{\mathrm{i}}$ represent the stage from k to h. Moreover, let L_{hk} serve as the division set between k and h. The definitions of the input variables, output variables, links, and carryover are outlined as follows:

Inputs and outputs

$$X_{iok}^{t} \epsilon R_{+} (i = 1, \ldots, m_k;\ o = 1, \ldots, n;\ k = 1, \ldots, K;\ t = 1, \ldots, T)$$

refers to input i at time period t for $\mathrm{DMU_o}$ division k; $X1_{iok}^{t}$. In the first stage, the production utilization stage, labor, and water supply are considered input variables. In the second stage, $X2^t_{iok}$, we have the governance stage, which uses the wastewater treatment input as the input variable.

$$Y^t_{rok} \epsilon R_+ (r = 1, \ldots, r_k;\ o = 1, \ldots, n;\ k = 1, \ldots, K;\ t = 1, \ldots, T)$$

refers to output r in time period t for DMU_o division k; $Y1^t_{rok}$. Furthermore, the GDP, per capita water usage, total agricultural water usage, and total industrial water usage are considered, similarly to the favorable output variables for the first stage.

$$B^t_{uok} (u = 1, \ldots, U_k;\ o = 1, \ldots, n;\ k = 1, \ldots, K;\ t = 1, \ldots, T)$$

The wastewater index, gas index, and solid waste are considered unfavorable output variables for the first stage.

$Y2^t_{rok}$ represents the favorable output variables for the second stage.

Exogenous variable

$E_{ajt} (a = 1 \ldots A)$ is the outside of a given economic model that often impacts the outcome of the model. Energy poverty is treated as an exogenous variable.

Links

$$Z^t_{do(kh)} \epsilon R_+ (d = 1 \ldots D; o = 1, \ldots, n; (kh) = 1, \ldots,\ link;\ t = 1, \ldots, T)$$

are the period t links from $\mathrm{DMU_o}$ division k to division h, with (kh) being the number of k to h links. $\mathrm{Z1^t_{do(12)}}$, the wastewater index, gas index, and solid waste index were selected as the link indicator in the production utilization stage and governance stage. $Z2^t_{do(21)}$ was selected as the link indicator in the governance stage and production utilization stage.

Carryovers

$$Z^{(t,t+1)}_{cok_l} \epsilon R_+ (c = 1 \ldots . C; o = 1, \ldots, n;\ k_l = 1, \ldots,\ ninput;\ \ t = 1, \ldots, T-1)$$

refers to the carryover of t to the t + 1 period from $\mathrm{DMU_o}$ division k to division h, with $\mathrm{L_k}$ being the number of carryover items in division k, $Z^{(t,t+1)}_{cok_l}$ (net fixed assets),

where $W^t (t = 1 \ldots T)$ is the weight to period t and $W^k (k = 1 \ldots k)$ is the weight to division k.

Other variables

(1) Meta-frontier (MF)

Suppose each of the DMU_p has an input and output at time period t and a carryover (link) to the next t + 1 time period.

Due to differences in management types, environment, and resources, all firms (N) were composed of decision-making units from g groups (N = N1 + N2 +. . ..+ NG), where $\mathrm{X_{io}}$ and $\mathrm{y_{ro}}$, respectively, represent the $\mathrm{i_{th}}$ input (i = 1, 2, . . ., m) and the rth final output (r = 1, 2, . . ., s) of the $\mathrm{j_{th}}$ unit (j = 1, 2, . . ., N). Under the common boundary, decision-making unit k can select the most favorable weights for its final outputs, thereby maximizing its efficiency value. Therefore, the efficiency of decision-making unit k under the common boundary can be determined through the following linear programming program.

The following is the non-oriented model:

(a) Objective function

Overall efficiency:

$$\theta^*_p = min \frac{\sum_{t=1}^{T} W^t \left[\sum_{k=1}^{K} W^k \left[1 - \frac{1}{m_k + ninput_k} \left(\sum_{g=1}^{G} \sum_{i=1}^{m_k} \frac{S^{t-}_{gipk}}{x^t_{gipk}} + \sum_{g=1}^{G} \sum_{k_l}^{ninput_k} \frac{s^{(t,t+1)}_{gcpk_l}}{z^{(t,t+1)}_{gcpk_l}} \right) \right] \right]}{\sum_{t=1}^{T} W^t \left[\sum_{k=1}^{K} W^k \left[1 + \frac{1}{r_k + U_k + link_k} \left(\sum_{g=1}^{G} \sum_{r=1}^{r_k} \frac{s^{t+}_{grpk}}{y^t_{grpk}} + \sum_{g=1}^{G} \sum_{u}^{U_k} \frac{s^{t-}_{gupk}}{B^t_{gupk}} + \sum_{g=1}^{G} \sum_{(kl)}^{link_k} \frac{s^t_{gdp(kl)}}{Z^t_{gdp(kl)}} \right) \right] \right]} \tag{5}$$

$$\sum_{t=1}^{T} W^t = 1;\ \sum_{k=1}^{K} W^k = 1$$

This is subject to the following:
Stage 1: Production utilization stage

$$X1^t_{gip1} = \sum_{g=1}^{G}\sum_{o=1}^{n} X1^t_{gio1}\lambda^t_{gio1} + s^{t-}_{gio1}(i = 1, \ldots, m_k,\ g = 1 \ldots..G)$$

$$y1^t_{grp1} = \sum_{g=1}^{G}\sum_{o=1}^{n} y1^t_{gro1}\lambda^t_{gro1} - s^{t+}_{gro1}(r = 1, \ldots, r_k,\ g = 1 \ldots..G)$$

$$B^t_{gup1} = \sum_{g=1}^{G}\sum_{o=1}^{n} B^t_{guo1}\lambda^t_{guo1} + s^{t-}_{guo1}(u = 1, \ldots, U_k,\ g = 1 \ldots..G)$$

$$Z1^t_{gdo(12)} = \sum_{g=1}^{G}\sum_{o=1}^{n} Z1^t_{gdo(12)}\lambda^{\mathrm{t}}_{\mathrm{gdo(12)}} + s^{t-}_{gdo(12)}\ (d = 1 \ldots D;\ g = 1 \ldots..G)$$

$$\lambda^{\mathrm{t}}_{\mathrm{gio1}} \geq 0,\ \ \lambda^{\mathrm{t}}_{\mathrm{gro1}} \geq 0;\ \lambda^t_{guo1} \geq 0;\ \lambda^{\mathrm{t}}_{\mathrm{gdo(12)}} \geq 0;\ s^{t-}_{gio1} \geq 0, ;\ s^{t+}_{gro1} \geq 0;\ s^{t-}_{guo1} \geq 0;\ s^{t-}_{gdo(12)} \geq 0$$

where $\mathrm{s}^{\mathrm{t-}}_{\mathrm{gio1}}$, $\mathrm{s}^{\mathrm{t+}}_{\mathrm{gro1}}$, and $\mathrm{s}^{\mathrm{t-}}_{\mathrm{guo1}}$ are Stage 1 of the input for the good output and bad output slacks. $\mathrm{s}^{\mathrm{t-}}_{\mathrm{gdo(12)}}$ represents the link slacks.

Stage 2: Governance stage

$$X2^t_{gip2} = \sum_{g=1}^{G}\sum_{o=1}^{n} X2^t_{gio2}\lambda^t_{gio2} + s^{t-}_{gio2}(i = 1, \ldots, m_k, g = 1 \ldots..G)$$

$$y2^t_{grp2} = \sum_{g=1}^{G}\sum_{o=1}^{n} y2^t_{gro2}\lambda^t_{gro2} - s^{t+}_{gro2}\ (r = 1, \ldots, r_k;\ g = 1 \ldots..G\,)$$

$$Z2^t_{gdo(21)} = \sum_{g=1}^{G}\sum_{o=1}^{n} Z2^t_{gdo(21)}\lambda^{\mathrm{t}}_{\mathrm{gdo(21)}} - s^{t+}_{gdo(21)}\ (d = 1 \ldots D;\ g = 1 \ldots..G)$$

$$\lambda^{\mathrm{t}}_{\mathrm{gio2}} \geq 0,\ \ \lambda^{\mathrm{t}}_{\mathrm{gro2}} \geq 0; \lambda^{\mathrm{t}}_{\mathrm{gdo(21)}} \geq 0, ;\ s^{t-}_{gio2} \geq 0,\ \ s^{t+}_{gro2} \geq 0;\ s^{t+}_{gdo(21)} \geq 0$$

s^{t-}_{gio2} *and* s^{t+}_{gro2} are stage 2 of input/output slacks. $s^{t+}_{gdo(21)}$ is link slacks.

$$e\lambda^t_k = 1\ (\forall k,\ \forall t);$$

$$\mathrm{E}^t_{\mathrm{gap}} = \sum_{g=1}^{G}\sum_{o=1}^{n} E^t_{gao}\lambda^t_{gao}(\ a = 1 \ldots..A;\ g = 1 \ldots..G)$$

$$Z^{(t,t+1)}_{gcpk_l} = \sum_{g=1}^{G}\sum_{o=1}^{n} Z^{(t,t+1)}_{gcok_l}\lambda^{\mathrm{t}}_{\mathrm{gco}k_l} + s^{t(t,t+1)}_{gcok_l}\ (\ c = 1 \ldots C; g = 1 \ldots..G)$$

$$\mathrm{s}^{t(t,t+1)}_{gok_l} \geq 0\ \ ;\ s^{t(t,t+1)}_{gcok_l}\ \textit{is carry over slacks.}$$

The period and division efficiencies are as follows:
(b1) Period efficiency:

$$\partial^*_p = min\frac{\sum_{k=1}^{K} W^k\left[1 - \frac{1}{m_k + ninput_k}\left(\sum_{g=1}^{G}\sum_{i=1}^{m_k}\frac{S^{t-}_{gipk}}{x^t_{gipk}} + \sum_{g=1}^{G}\sum_{k_l}^{ninput_k}\frac{s^{(t,t+1)}_{gcpk_l}}{z^{(t,t+1)}_{gcpk_l}}\right)\right]}{\sum_{k=1}^{K} W^k\left[1 + \frac{1}{r_k + U_k + link_k}\left(\sum_{g=1}^{G}\sum_{r=1}^{r_k}\frac{s^{t+}_{grpk}}{y^t_{grpk}} + \sum_{g=1}^{G}\sum_{u}^{U_k}\frac{s^{t-}_{gupk}}{B^t_{gupk}} + \sum_{g=1}^{G}\sum_{(kl)}^{link}\frac{s^t_{gdp(kl)}}{Z^t_{gdp(kl)}}\right)\right]} \quad (6)$$

(b2) Division efficiency:

$$\varphi^*_p = min\frac{\sum_{t=1}^{T} W^t\left[1 - \frac{1}{m_k + ninput_k}\left(\sum_{g=1}^{G}\sum_{i=1}^{m_k}\frac{S^{t-}_{gipk}}{x^t_{gipk}} + \sum_{g=1}^{G}\sum_{k_l}^{ninput_k}\frac{s^{(t,t+1)}_{gcpk_l}}{z^{(t,t+1)}_{gcpk_l}}\right)\right]}{\sum_{t=1}^{T} W^t\left[1 + \frac{1}{r_k + U_k + link_k}\left(\sum_{g=1}^{G}\sum_{r=1}^{r_k}\frac{s^{t+}_{grpk}}{y^t_{grpk}} + \sum_{g=1}^{G}\sum_{u}^{U_k}\frac{s^{t-}_{gupk}}{B^t_{gupk}} + \sum_{g=1}^{G}\sum_{(kl)}^{link_k}\frac{s^t_{gdp(kl)}}{Z^t_{gdp(kl)}}\right)\right]} \quad (7)$$

(b3) Division period efficiency:

$$\rho_p^* = min\frac{\left[1 - \frac{1}{m_k+ninput_k}\left(\sum_{g=1}^{G}\sum_{i=1}^{m_k}\frac{S_{gipk}^{t-}}{x_{gipk}^{t}} + \sum_{g=1}^{G}\sum_{k_l}^{ninput_k}\frac{s_{gcpk_l}^{(t,t+1)}}{z_{gcpk_l}^{(t,t+1)}}\right)\right]}{\left[1 + \frac{1}{r_k+U_k+link_k}\left(\sum_{g=1}^{G}\sum_{r=1}^{r_k}\frac{s_{grpk}^{t+}}{y_{grpk}^{t}} + \sum_{g=1}^{G}\sum_{u}^{U_k}\frac{s_{gupk}^{t-}}{B_{gupk}^{t}} + \sum_{g=1}^{G}\sum_{(kl)}^{link_k}\frac{s_{gdp(kl)}^{t}}{Z_{gdp(kl)}^{t}}\right)\right]} \quad (8)$$

From the above, the overall efficiency, period efficiency, division efficiency, and division period efficiency can be obtained using the meta-frontier model.

(2) Group frontier (GF)

As each DMU under the group frontier chooses the most favorable final weighted output, the DMU efficiencies under the group frontier are solved using the following equations:
(a) The objective function
Overall efficiency:

$$\theta_p^{g*} = min\frac{\sum_{t=1}^{T}W^t\left[\sum_{k=1}^{K}W^k\left[1 - \frac{1}{m_k+ninput_k}\left(\sum_{i=1}^{m_k}\frac{S_{ipk}^{t-}}{x_{ipk}^{t}} + \sum_{k_l}^{ninput_k}\frac{s_{cpk_l}^{(t,t+1)}}{z_{cpk_l}^{(t,t+1)}}\right)\right]\right]}{\sum_{t=1}^{T}W^t\left[\sum_{k=1}^{K}W^k\left[1 + \frac{1}{r_k+U_k+link_k}\left(\sum_{r=1}^{r_k}\frac{s_{rpk}^{t+}}{y_{rpk}^{t}} + \sum_{u}^{U_k}\frac{s_{upk}^{t-}}{B_{upk}^{t}} + \sum_{(kl)}^{link_k}\frac{s_{dp(kl)}^{t}}{Z_{dp(kl)}^{t}}\right)\right]\right]} \quad (9)$$

This is subject to the following:
Stage 1: Production utilization stage

$$X1_{ip1}^{t} = \sum_{o=1}^{n}X1_{io1}^{t}\lambda_{io1}^{t} + s_{io1}^{t-}(i = 1,\ldots,m_k)$$
$$y1_{rp1}^{t} = \sum_{o=1}^{n}y1_{ro1}^{t}\lambda_{ro1}^{t} - s_{ro1}^{t+}(r = 1,\ldots,r_k)$$
$$B_{up1}^{t} = \sum_{o=1}^{n}B_{uo1}^{t}\lambda_{uo1}^{t} + s_{uo1}^{t-}(u = 1,\ldots,U_k)$$
$$Z_{dp(12)}^{t} = \sum_{o=1}^{n}Z_{do(12)}^{t}\lambda_{\mathrm{do(12)}}^{\mathrm{t}} + s_{do(12)}^{t-}\ (\mathrm{d} = 1\ldots\mathrm{D})$$
$$\lambda_{\mathrm{io1}}^{\mathrm{t}} \geq 0,\ \ \lambda_{\mathrm{ro1}}^{\mathrm{t}} \geq 0;\ \lambda_{uo1}^{t} \geq 0;\ \lambda_{\mathrm{do(12)}}^{\mathrm{t}} \geq 0;\ s_{io1}^{t-} \geq 0,\ \ s_{ro1}^{t+} \geq 0;\ s_{uo1}^{t-}\ \geq 0; s_{do(12)}^{t-} \geq 0;$$

where $\mathrm{s_{io1}^{t-}, s_{ro1,}^{t+}}$ and $\mathrm{s_{uo1}^{t-}}$ are Stage 1 of the input for good output and bad output slacks. $\mathrm{s_{do(12)}^{t-}}$ represents the link slacks.
Stage 2: Governance stage

$$X2_{ip2}^{t} = \sum_{o=1}^{n}X2_{io2}^{t}\lambda_{io2}^{t} + s_{io2}^{t-}(i = 1,\ldots,m_k)$$
$$y2_{rp2}^{t} = \sum_{o=1}^{n}y2_{ro2}^{t}\lambda_{ro2}^{t} - s_{ro2}^{t+}\left(r = 1,\ldots,r_k\right)$$
$$Z_{dp(21)}^{t} = \sum_{o=1}^{n}Z_{do(21)}^{t}\lambda_{\mathrm{do(21)}}^{\mathrm{t}} - s_{do(21)}^{t+}\ (\mathrm{d} = 1\ldots\mathrm{D})$$
$$\lambda_{io2}^{\mathrm{t}} \geq 0,\ \lambda_{ro2}^{\mathrm{t}} \geq 0;\ \lambda_{\mathrm{do(21)}}^{\mathrm{t}} \geq 0;\ s_{io2}^{t-} \geq 0,\ \ s_{ro2}^{t+} \geq 0;\ s_{do(21)}^{t+} \geq 0$$
$$s_{io2}^{t-}\ and\ s_{ro2}^{t+}\ \text{are stage 2 of input/output slacks.;}\ s_{do(21)}^{t+}\text{is link slacks.}$$
$$e\lambda_k^t = 1(\forall k,\ \forall t);$$
$$\mathrm{E}_{\mathrm{ap}}^{t} = \sum_{o=1}^{n}E_{ao}^{t}\lambda_{ao}^{t}(\ a = 1\ldots..A)$$
$$Z_{cpk_l}^{(t,t+1)} = \sum_{o=1}^{n}Z_{cok_l}^{(t,t+1)}\lambda_{\mathrm{cok}_l}^{\mathrm{t}} + s_{cok_l}^{t(t,t+1)}\ \ (\mathrm{c} = 1\ldots\mathrm{C})$$
$$s_{cok_l}^{t(t,t+1)} \geq 0;\ s_{cok_l}^{t(t,t+1)}\ is\ carry\ over\ slacks.$$

(b) Period and division efficiencies

The period and division efficiencies are as follows:

(b1) Period efficiency:

$$\partial_p^* = min\frac{\sum_{k=1}^{K} W^k\left[1-\frac{1}{m_k+ninput_k}\left(\sum_{i=1}^{m_k}\frac{S_{ipk}^{t-}}{x_{ipk}^t}+\sum_{k_l}^{ninput_k}\frac{s_{cpk_l}^{(t,t+1)}}{z_{cpk_l}^{(t,t+1)}}\right)\right]}{\sum_{k=1}^{K} W^k\left[1+\frac{1}{r_k+U_k+link_k}\left(\sum_{r=1}^{r_k}\frac{s_{rpk}^{t+}}{y_{rpk}^t}+\sum_{u}^{U_k}\frac{s_{upk}^{t-}}{B_{upk}^t}+\sum_{(kl)}^{link}\frac{s_{dp(kl)}^t}{Z_{dp(kl)}^t}\right)\right]} \tag{10}$$

(b2) Division efficiency:

$$\varphi_p^* = min\frac{\sum_{t=1}^{T} W^t\left[1-\frac{1}{m_k+ninput_k}\left(\sum_{i=1}^{m_k}\frac{S_{ipk}^{t-}}{x_{ipk}^t}+\sum_{k_l}^{ninput_k}\frac{s_{cpk_l}^{(t,t+1)}}{z_{cok_l}^{(t,t+1)}}\right)\right]}{\sum_{t=1}^{T} W^t\left[1+\frac{1}{r_k+U_k+link_k}\left(\sum_{r=1}^{r_k}\frac{s_{rpk}^{t+}}{y_{rpk}^t}+\sum_{u}^{U_k}\frac{s_{upk}^{t-}}{B_{upk}^t}+\sum_{(kl)}^{link}\frac{s_{dp(kl)}^t}{Z_{dp(kl)}^t}\right)\right]} \tag{11}$$

(b3) Division period efficiency:

$$\rho_p^* = min\frac{1-\frac{1}{m_k+ninput_k}\left(\sum_{i=1}^{m_k}\frac{S_{ipk}^{t-}}{x_{ipk}^t}+\sum_{k_l}^{ninput_k}\frac{s_{cpk_l}^{(t,t+1)}}{z_{cpk_l}^{(t,t+1)}}\right)}{1+\frac{1}{r_k++U_k+link_k}\left(\sum_{r=1}^{r_k}\frac{s_{rpk}^{t+}}{y_{rpk}^t}+\sum_{u}^{U_k}\frac{s_{upk}^{t-}}{B_{upk}^t}+\sum_{(kl)}^{link}\frac{s_{dp(kl)}^t}{Z_{dp(kl)}^t}\right)} \tag{12}$$

From the above results, the overall efficiency, period efficiency, division efficiency, and division period efficiency are obtained.

(3) Technology gap ratio (TGR)

As the meta-frontier model contains g groups, the technical efficiency of the meta-frontier (MFE) was found to be less than the technical efficiency of the group frontier (GFE). The ratio value, or the technology gap ratio (TGR), is as follows:

$$\text{TGR} = \frac{\theta_p^*}{\theta_p^{g*}} = \frac{MFE}{GFE} \tag{13}$$

3.1.3. Total Factor Efficiency (TFE)

The sub-efficiency values of various variables in this study were calculated based on the total factor efficiency metric, as expressed in the following formula:

Applicable to the input and unfavorable output variables as follows:

$$\text{TFE} = \frac{\text{Target Input}}{\text{Actual Input}} \tag{14}$$

Applicable to the favorable output variables as follows:

$$\text{TFE} = \frac{\text{Actual Output}}{\text{Target Output}} \tag{15}$$

If the total factor efficiency value is 1, it indicates an achievement in the efficiency benchmarks; conversely, values below 1 signify the presence of excess inputs or output deficiencies, thereby suggesting room for improvement.

3.2. Data Source

This study's research concept was illustrated in the model diagram based on the model construction and method description provided above (Figure 1). The diagram introduces the concept of cycles, thereby facilitating the linkage from period t to period $t + 1$ through link variables. By selecting fixed assets as carryover variables, the model simulates the transfer and utilization of resources in the cyclic process more accurately. This construction aids in conducting a comprehensive and efficient system evaluation. The division of sustainable water resource utilization stages is primarily grounded in two fundamental facets of water resource management: resource acquisition and utilization and resource protection and management. The initial stage involves the extraction, utilization, and allocation of water resources, which encompasses agricultural, industrial, and urban water activities. The subsequent stage pertains to the efficient protection, management, and governance of water resources, which encompasses wastewater treatment and other related measures.

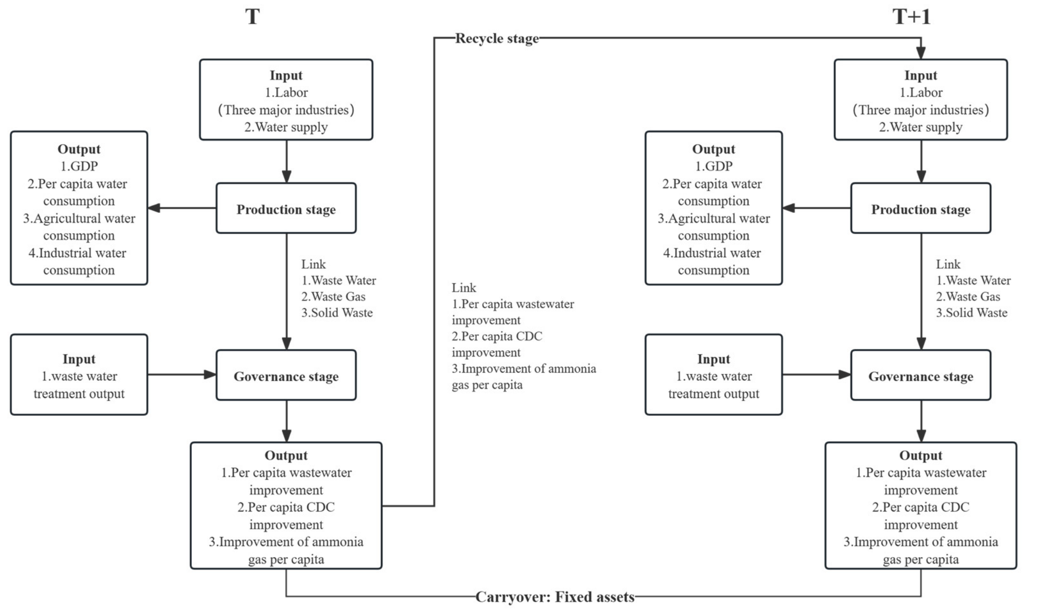

Figure 1. The research model.

Table 2 presents the variables used in this research model. Previous studies have employed diverse variables to evaluate inputs and outputs in the water resource sustainability process. In this study, the entropy weight method was utilized to measure the output variables and link variables. When conducting DEA calculations, the S1 output index and S2 output index served as indicators.

Table 2. Variable description.

		Variable	Description	Unit
Stage 1	Input	Labor	Total employment	Thousands of people
		Water supply	Annual water supply	Million cubic meters
	Output	GDP	Gross domestic product	CNY one hundred million
		S1 output index	Per capita water consumption	Cubic meter per person
			Adjusted agricultural increase Adjusted industrial increase	CNY per cubic meter

Table 2. *Cont.*

		Variable	Description	Unit
Stage 2	Input	Wastewater treatment input	Government financial investment in sewage treatment	CNY ten thousand
	Output	S2 output index	Per capita wastewater improvement	Tons per person
			COD improvement per capita Improvement in ammonia nitrogen per capita	Kilogram per person
	Link	Wastewater index	Total COD emissions in the current year Total ammonia nitrogen emissions for the year	Ten thousand tons
		Gas index	Total sulfur dioxide emissions from exhaust gases Total nitrogen oxide emissions from exhaust gases Total amount of smoke and dust emitted in exhaust gas	Ten thousand tons
		Solid waste	General industrial solid amount of waste produced	Ten thousand tons
	Exogenous variable	Energy poverty	Calculated according to the three-level index constructed by Yi-Ming Wei and Hua Liao (2018)	
	Carryover	Fixed assets	Fixed assets	CNY 1000

Note: Data sources: National Bureau of Statistics of the People's Republic of China, China Energy Yearbook, China Rural Statistical Yearbook, and China Regional Economic Statistical Yearbook.

To analyze the technological boundaries in different regions of China and to formulate subsequent policy recommendations tailored to the characteristics of each region, this study divides the provinces, municipalities, and autonomous regions of China into eastern, central, and western regions based on the classification standards provided by the National Bureau of Statistics, as outlined in Table 3.

Table 3. Area classification.

Area	Number	Provinces
East	1	Beijing, Fujian, Guangdong, Hainan, Hebei, Jiangsu, Liaoning, Shandong, Shanghai, Tianjin and Zhejiang
Middle	2	Anhui, Heilongjiang, Henan, Hubei, Hunan, Jiangxi, Jilin and Shanxi
West	3	Chongqing, Gansu, Guangxi, Guizhou, Inner Mongolia, Ningxia, Qinghai, Shaanxi, Sichuan, Tibet, Xinjiang and Yunnan

Note: Data sources: National Bureau of Statistics of the People's Republic of China. Available online: http://www.stats.gov.cn/xxgk/sjfb/zxfb2020/201912/t20191219_1767580.html (accessed on 20 June 2023).

The regions included in this study are indicated in Figure 2 (excluding the areas shaded in gray).

Figure 2. Map of the study area location.

4. Result Analysis

4.1. Total Efficiency Analysis

Before conducting a detailed analysis of the stages and individual input–output factors, we first analyzed the total efficiency scores for the 29 provinces with and without considering the impact of the exogenous variable. The results are presented in Figure 3.

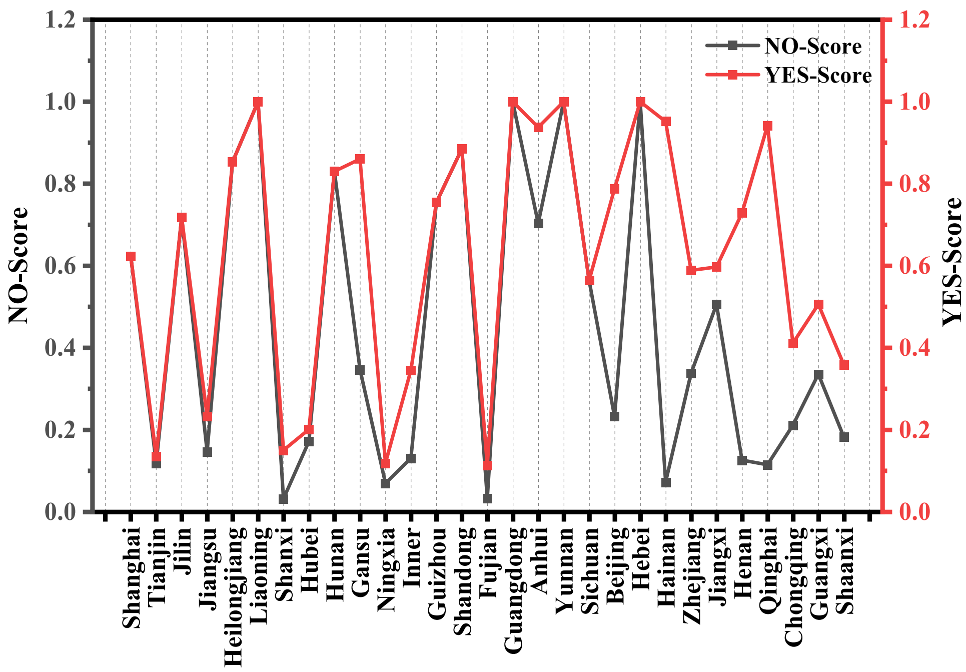

Figure 3. Total efficiency scores of the provinces and cities in the line chart.

As shown in the figure, only four provinces—Liaoning, Guangdong, Yunnan, and Hebei—consistently maintain an ideal state. Overall, there is still significant room for improvement. Notably, provinces and municipalities such as Beijing, Shanghai, and Zhejiang, which have well-developed infrastructure and rank high in economic development, have not achieved a moderate level of water resource utilization efficiency, with scores below 0.600. Furthermore, even coastal cities with robust economies and abundant water resources, such as Tianjin, Jiangsu, and Fujian, have not attained efficiency scores exceeding 0.400.

According to the results of the Shapiro–Wilk analysis, it is evident that the total efficiency values obtained for each province and municipality, whether considering the exogenous variable or not, do not follow a normal distribution. Therefore, the paired-sample Wilcoxon signed-rank test method was employed to examine whether there is a significant difference in the total efficiency of each province and municipality when considering the exogenous variable and when not considering it.

The results of the paired-sample Wilcoxon test (Table 4) indicate that there is a significant difference between the NO-Score and the YES-Score. Including the exogenous variable, energy poverty, resulted in a moderate difference in the overall efficiency scores for water resource utilization. To ensure the analysis's accuracy, we examined the efficiency of water resource utilization for each province and municipality, which was achieved by taking into account the impact of the exogenous variable.

Table 4. Paired-sample Wilcoxon signed-rank test for total efficiency.

Pairing Variable	Median ± SD			z	df	P	Cohen's d
	Pair 1	Pair 2	Pairing Difference				
NO-Score-YES-Score	0.338 ± 0.35	0.718 ± 0.309	−0.081 ± 0.254	3.808	28	0.000 ***	0.532

Note: *** represent significance levels of 1%, respectively.

To provide targeted recommendations, the following sections of this paper will analyze the stage-wise efficiency scores and technological boundaries, thereby aiming to arrive at practical conclusions.

4.2. Stage Efficiency Analysis

In this section, we will continue to explore the relationship between the production and governance stages, as well as the interaction between the two stages, through an analysis of efficiency scores.

Next, we compare the effect of whether exogenous variables are introduced or not on the efficiency values of the two phases through bar charts (Figures 4 and 5). In addition, the trends of the two groups of data with and without exogenous variables were found to be incredibly similar for both the production and governance stages; overall, the efficiency values of the group with exogenous variables were more favorable, but the difference was more significant for the production stage, where the impact of the exogenous variables was more pronounced for the production stage.

It is evident that all of the provinces' efficiency values in the production stage were not lower than those in the governance stage. Among them, Beijing, Qinghai, Chongqing, Hainan, Hunan, Heilongjiang, and Guangdong had higher average values and better synergies between the two stages; however, Shanghai, Shandong, Jiangsu, Zhejiang, and Fujian, which are coastal provinces with a more developed economy, had particularly low efficiency performances (less than 0.600) in the governance stage, while the efficiency performance in the production stage tended to be ideal.

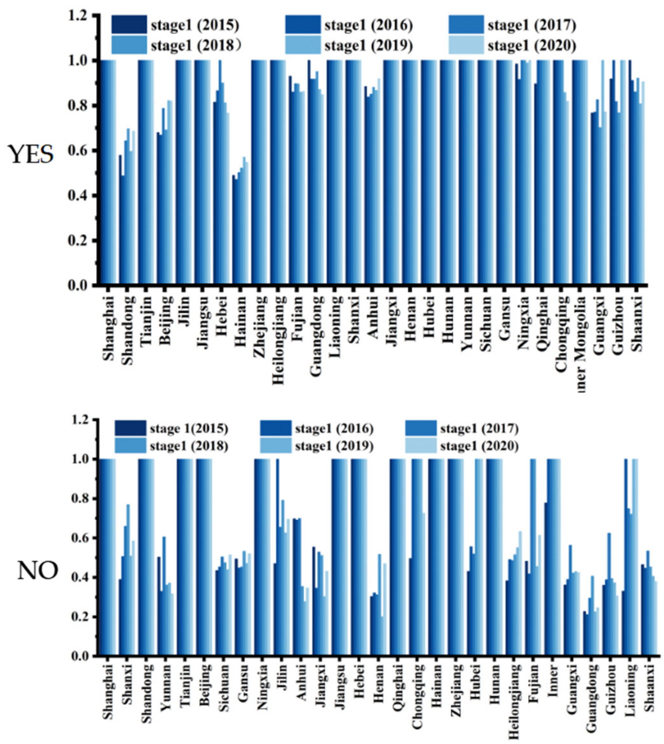

Figure 4. Comparison of the production stage efficiency scores with and without consideration of the exogenous variables.

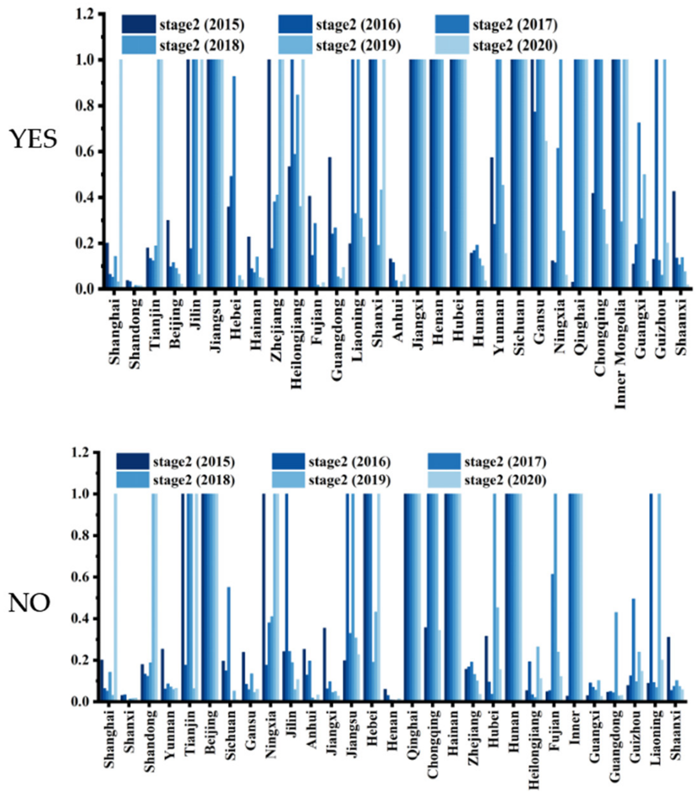

Figure 5. Comparison of the governance stage efficiency scores with and without consideration of the exogenous variables.

Figure 6 shows the changes in the water sustainability efficiency score of each province between 2015 and 2020. There are only four provinces (in addition to Shanghai, Shandong, and Ningxia) that have consistently maintained the desired level, showing a benign trend. The efficiency scores of Sichuan, Anhui, Jiangxi, Hubei, Fujian, Guangxi, and Shaanxi all showed an overall decreasing trend, which may require these provinces to make certain corrections in macropolicies or resource allocation to promote sustainable water resource development. In addition, Shandong, Yunnan, Gansu, Henan, and Zhejiang have stable but low efficiency scores, and they may need to break down technical or management constraints to improve overall efficiency performance.

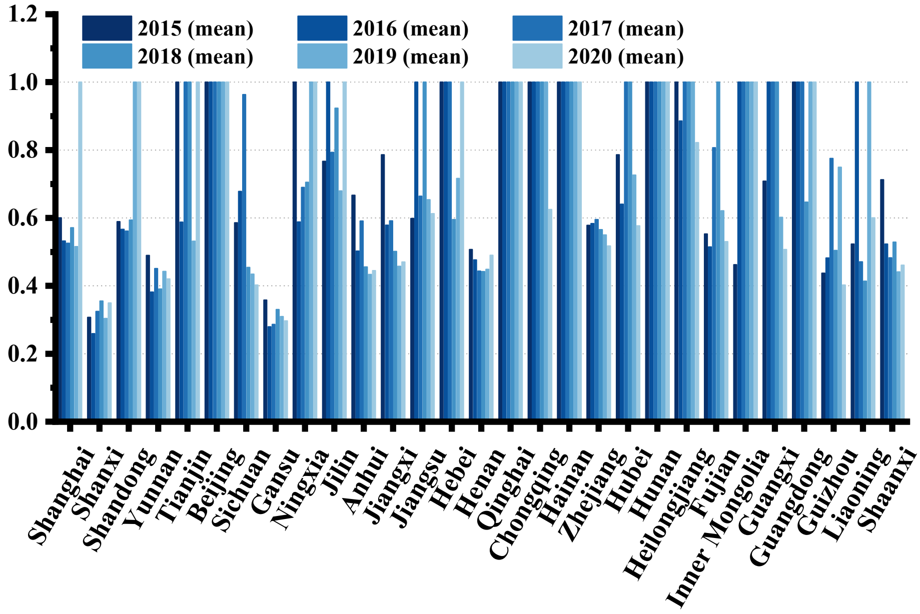

Figure 6. Changes in the sustainable efficiency value of water resources by province.

The results of the Shapiro–Wilk analysis indicated that the efficiency scores for both stages, whether considering the exogenous variable "energy poverty" or not, did not follow a normal distribution. Therefore, we employed the paired-sample Wilcoxon signed-rank test to examine whether there are significant differences in the efficiency scores between the two-stage assessments when considering the exogenous variable and when not considering it.

The paired-sample Wilcoxon signed-rank test results (Table 5) indicated that there is a significant difference in the water resource production stage efficiency scores before and after considering the exogenous variable. From the above test results, we can conclude that including the exogenous variable significantly affects the efficiency score calculations for both the production and governance stages. When discussing the topic of sustainable water resource utilization, incorporating considerations of energy scarcity can enhance the practicality of the conclusions drawn. In the subsequent analysis in this section, we will use the efficiency scores calculated with consideration of the exogenous variable.

Table 5. Paired-sample Wilcoxon signed-rank test for Stage Efficiency 1.

Pairing Variable	Median ± SD			z	df	P	Cohen's d
	Pair 1	Pair 2	Pairing Difference				
Stage1 (NO)–Stage1 (YES)	0.751 ± 0.263	1.000 ± 0.122	−0.117 ± 0.223	3.724	28	0.000 ***	0.987
Stage2 (NO)–Stage2 (YES)	0.306 ± 0.344	0.510 ± 0.334	−0.011 ± 0.229	3.808	28	0.000 ***	0.350

Note: *** represent significance levels of 1%, respectively.

Similarly, due to the data not following a normal distribution, we will employ a paired-sample Wilcoxon signed-rank test to examine whether there are significant differences in the efficiency scores between the two stages.

The paired-sample Wilcoxon signed-rank test (Table 6) results indicated that, based on the variable Stage 1 (mean) paired with Stage 2 (mean), the significance p-value was 0.000 ***. This suggested a significant difference between the efficiency scores of the production and governance stages. The magnitude of this difference, as measured by Cohen's d value, was 1.618, which is extremely large. This analysis result indicated that, in water resource utilization, the production and governance stages are not developing in parallel. From the average values, we can see that the efficiency level of the production stage is significantly higher than that of the governance stage. This finding aligns with the conclusions drawn in the previous section.

Table 6. Paired-sample Wilcoxon signed-rank test for Stage Efficiency 2.

Pairing Variable	Median ± SD			z	df	P	Cohen's d
	Pair 1	Pair 2	Pairing Difference				
Stage1 (mean)–Stage2 (mean)	1.000 ± 0.122	0.510 ± 0.334	0.423 ± 0.272	4.372	28	0.000 ***	1.618

Note: *** represent significance levels of 1%, respectively.

4.3. Input–Output Factor Efficiency Analysis

In the previous section, we empirically analyzed how including an exogenous variable significantly affects efficiency value calculations. To arrive at more practical conclusions, the input–output factor efficiency scores used in this section were derived from models that consider the exogenous variable "energy poverty".

Firstly, most of the provinces and municipalities demonstrated relatively ideal utilization efficiency for the input factor "Labor" in the production stage, as shown in Figure 7. Nineteen of them consistently maintained ideal efficiency in utilizing this factor over the six years from 2015 to 2020. In the remaining regions, nine provinces and municipalities exhibited fluctuating efficiency scores at a relatively high level.

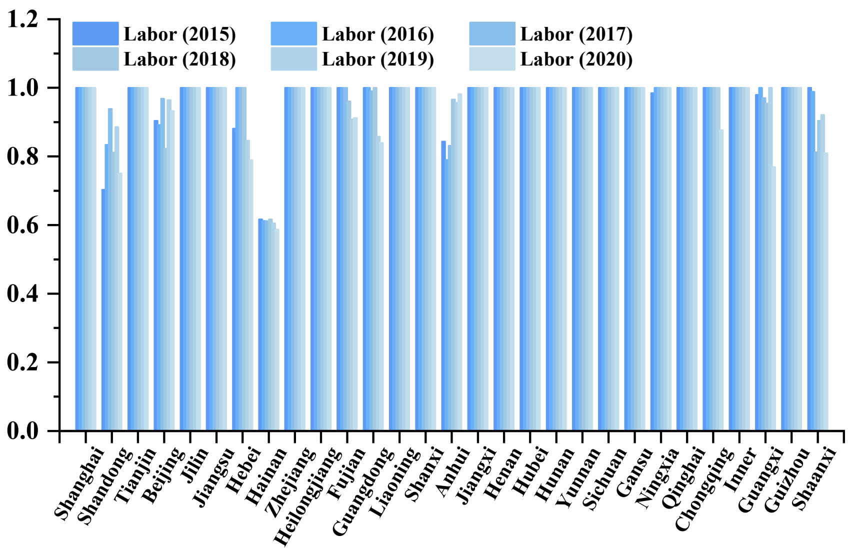

Figure 7. Labor efficiency score bar chart for 2015–2020.

For the input factor "water supply" in the production stage, as shown in Figure 8, 16 of the provinces and municipalities consistently maintained ideal efficiency levels over the six years. While not consistently ideal, six of the provinces and municipalities exhibited efficiency score changes that remained relatively high. Among them, the Beijing and Guangxi provinces showed a noticeable upward trend in efficiency scores, with the Guangxi Province reaching near-ideal efficiency scores in 2019–2020. However, Beijing's highest efficiency score still fell within the moderate range, thus indicating significant room for improvement.

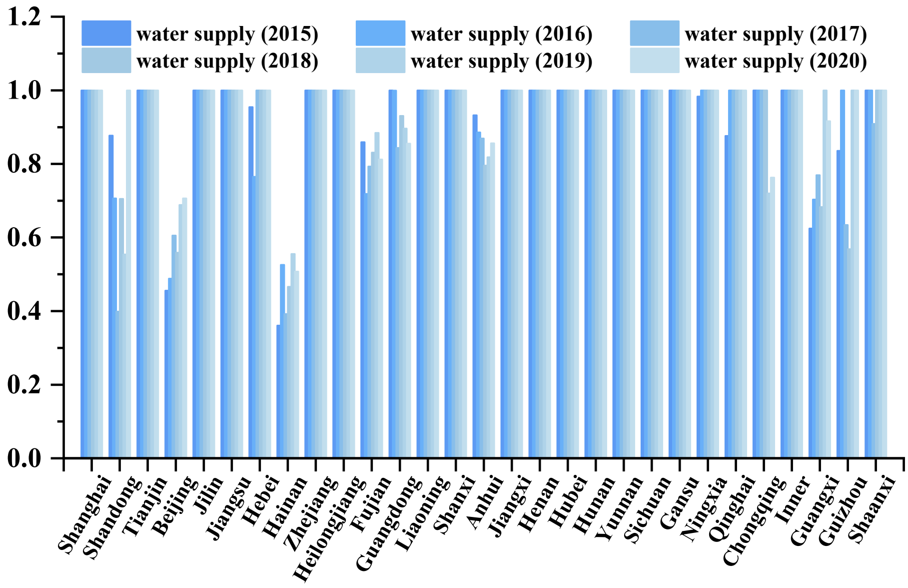

Figure 8. Water supply efficiency score bar chart for 2015–2020.

For one of the output factors in the production stage—GDP—as shown in Figure 9, most of the provinces and municipalities included in this study maintained ideal efficiency scores over the six years. Only three regions experienced fluctuations below the ideal level, but these fluctuations remained relatively high.

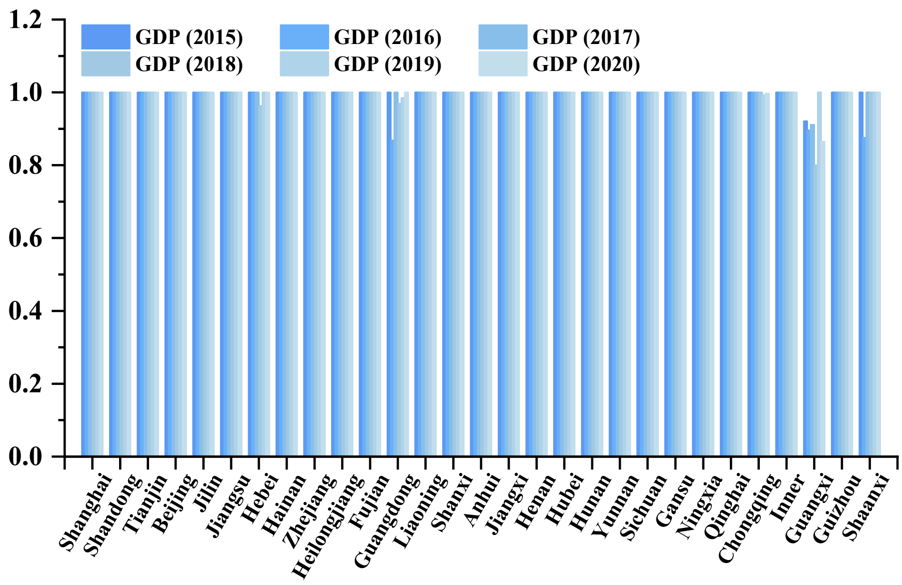

Figure 9. GDP efficiency score bar chart for 2015–2020.

Another part of the output factors in the production stage was the first-stage output indicator, S1, which was obtained using the entropy weight method, as shown in Figure 10. There were a total of 21 provinces and municipalities that consistently maintained ideal first-stage output during these six years. Additionally, while not consistently maintaining the ideal state, six of the provinces had fluctuating efficiency scores that remained at relatively high levels.

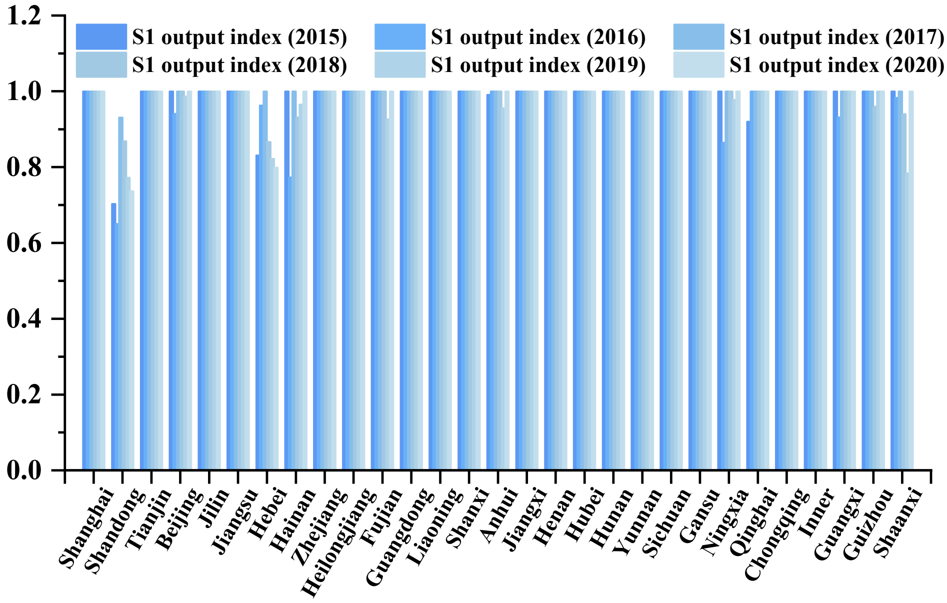

Figure 10. S1 output index efficiency score bar chart for 2015–2020.

Regarding the "wastewater treatment input" factor in the governance stage (Figure 11), only the Jiangsu, Jiangxi, Hubei, and Sichuan provinces consistently maintained ideal efficiency scores over the six years. Most of the other provinces experienced significant abnormal changes in their numerical values, possibly due to changes in their input and allocation policies, changes in their immature technology and management models, or significant external factors influencing governance efficiency.

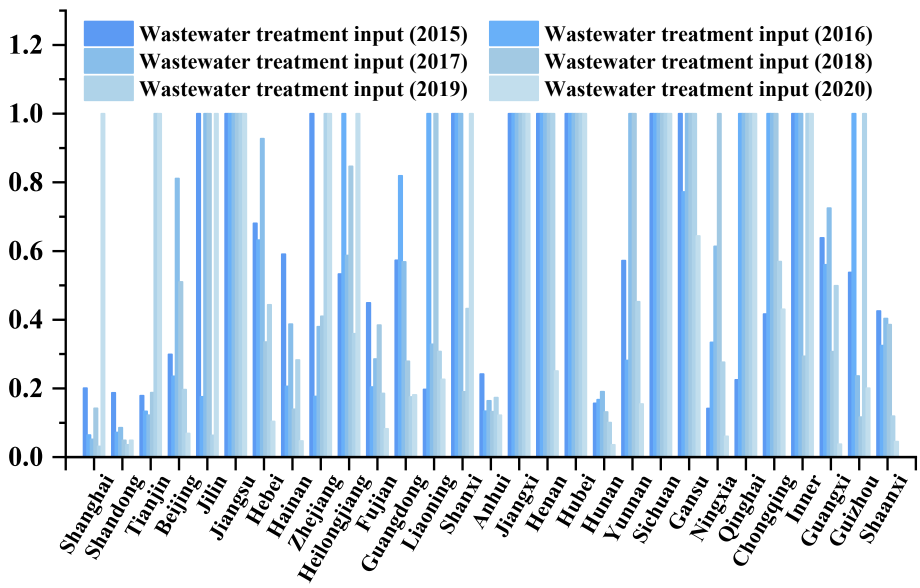

Figure 11. Wastewater treatment input efficiency score bar chart for 2015–2020.

The output factor in the governance stage was the output index S2, which was obtained using the entropy weighting method, as shown in Figure 12. The efficiency scores of 16 provinces and cities consistently remained ideal. However, five of the provinces—Beijing, Fujian, Guangdong, Chongqing, and Shaanxi—experienced a sustained decline in efficiency.

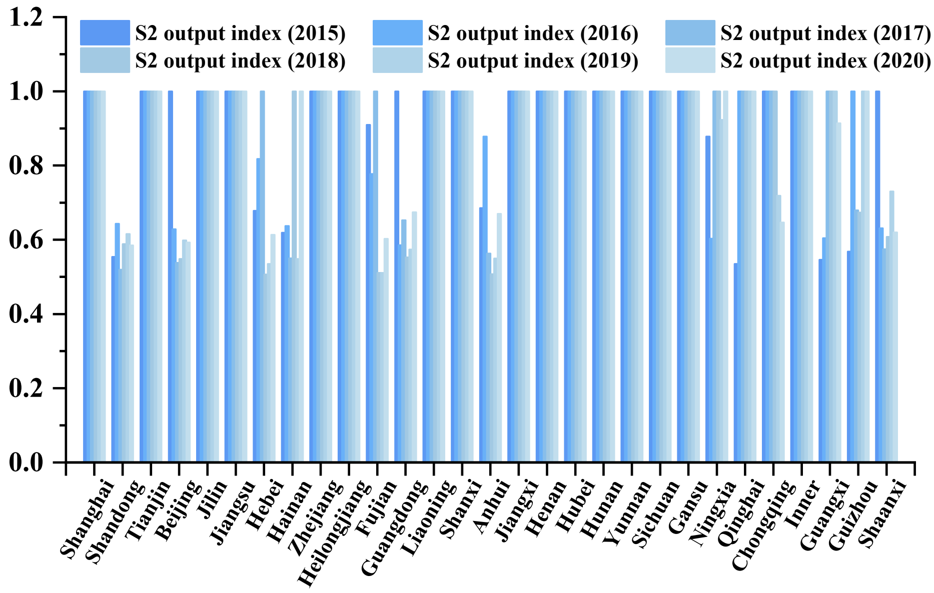

Figure 12. S2 output index efficiency score bar chart for 2015–2020.

In summary, among these input–output factors, the efficiency of labor, GDP, and the output index in the production stage generally exhibited a relatively ideal state. The efficiency of water supply and the output index in the governance stage also reached high levels in more than half of the regions. However, when it comes to the input of wastewater treatment, only four provinces and cities maintained consistently ideal efficiency. In contrast, other provinces and cities even showed persistently low efficiency levels below 0.400, with significant fluctuations observed in this indicator on several occasions. This may be related to China's policies regarding the allocation of resources for water resource management or related management models. To provide a more intuitive exploration of the efficiency of the different factors in each province and city, a radar chart was created based on the efficiency scores of various factors in 2020.

According to the radar chart (Figure 13), it is evident that the factor with the highest fluctuation in efficiency levels among the different provinces and cities, as well as the lowest overall efficiency, was the wastewater treatment input. Notably, Gansu, Yunnan, Henan, Anhui, Liaoning, Guangdong, Fujian, Hainan, Beijing, Shandong, Shaanxi, Guizhou, Guangxi, and Ningxia were all significantly constrained by this indicator. Provinces significantly constrained by these factors in the governance stage also exhibit substantial overlap. In water resource utilization, these regions may face certain issues related to the technical models and management processes in the governance stage.

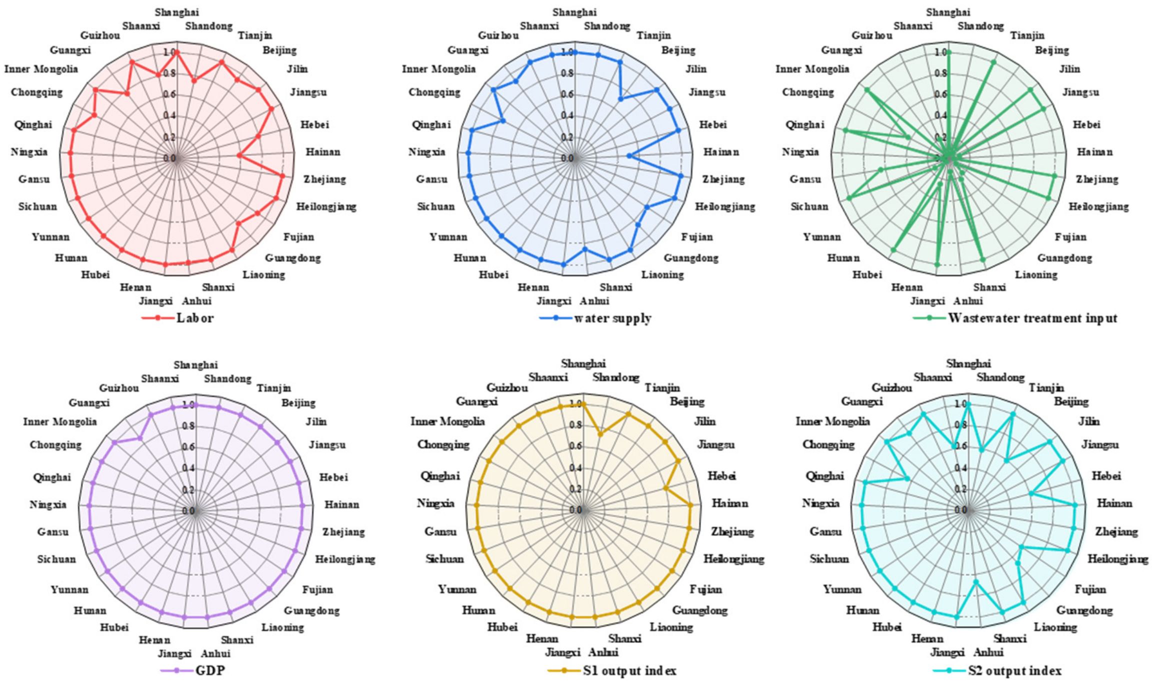

Figure 13. Factor utilization efficiency radar map.

4.4. Technology Frontier Analysis

In this section, we focus on examining technological boundaries and exploring the impact of technological differences. Including all the DMUs within a single boundary for efficiency comparisons is unfair. Therefore, this paper adopts a reasonable approach and divides all DMUs into three groups based on the geographical classification of eastern, central, and western regions.

4.4.1. Group Frontier and Meta-Frontier Analysis

We conducted a comparative analysis of the technical efficiency in water resource production and the governance stages under both the group frontier and meta-frontier frameworks to draw further conclusions (Table 7).

From the perspective of the production stage of water resource utilization, the transition from GF (group frontier) to MF (meta-frontier) had minimal impact on the eastern region when considering the technical differences between different regions. However, the central and western regions experienced significant declines in technical efficiency. There was over 10% improvement potential in terms of optimal efficiency levels. The results also indicated an enormous technical gap (0.119) between the central region and the potential common frontier.

Regarding the potential optimal efficiency levels, the eastern, central, and western regions indicated improvement potentials of 37.8%, 66.3%, and 49.7%, respectively. Similar to the production stage, if technical differences are not considered, the technical efficiency of each region would be significantly overestimated. Therefore, within the meta-frontier framework, which accounts for technical differences, we can measure the technical efficiency of different processes of water resource utilization more accurately.

Table 7. Group frontier and meta-frontier efficiency for the eastern, median, and western regions from 2015 to 2020.

			Stage1			
Cluster	1		2		3	
Year	GF	MF	GF	MF	GF	MF
2015	0.986	0.993	1.000	0.899	0.984	0.865
2016	1.000	0.994	1.000	0.850	1.000	0.869
2017	1.000	0.986	1.000	0.885	0.989	0.898
2018	0.982	0.982	1.000	0.904	0.982	0.874
2019	1.000	0.999	1.000	0.865	1.000	0.887
2020	1.000	1.000	1.000	0.886	0.985	0.863
Mean	0.995	0.992	1.000	0.881	0.990	0.876
			Stage2			
Cluster	1		2		3	
Year	GF	MF	GF	MF	GF	MF
2015	0.878	0.578	1.000	0.453	0.805	0.487
2016	0.882	0.648	1.000	0.302	0.866	0.518
2017	0.801	0.617	1.000	0.433	0.795	0.632
2018	0.915	0.604	0.968	0.348	0.813	0.509
2019	0.783	0.581	1.000	0.259	0.893	0.509
2020	0.811	0.705	1.000	0.226	0.917	0.361
Mean	0.845	0.622	0.995	0.337	0.848	0.503

4.4.2. Technology Gap Ratio Analysis

The TGR score reflects the magnitude of the gap between the group technical frontier and the meta-technical frontier. A higher TGR score indicates a smaller gap. In extreme cases, a TGR of 1 means unity between the group's technical and meta-technical frontiers. At the same time, a TGR score of zero represents the maximum disparity between the two [47]. The TGR scores for the eastern, central, and western regions over the six years from 2015 to 2020 are shown in Table 8.

Table 8. TGR analysis for the three regions from 2015 to 2020.

Cluster	**2015**	**2016**	**2017**	**2018**	**2019**	**2020**	**Average**
1	0.843	0.877	0.891	0.840	0.887	0.942	0.880
2	0.676	0.576	0.659	0.635	0.562	0.556	0.611
3	0.766	0.750	0.854	0.772	0.738	0.656	0.756

The data results revealed that the TGR score for the eastern region showed a noticeable upward trend over these six years and reached 0.9422 in 2020. This implies that the group frontier technical efficiency in the eastern region is closer to the meta-frontier compared to the central and western regions. It also suggests that the eastern region may exhibit better sustainability performance than the central and western regions.

The TGR gap reflects the differing production technology standards, where higher TGR scores indicate that the producers' technology is closer to the meta-frontier. Therefore, we further analyzed the production efficiency in different regions by comparing the stage-specific TGR with efficiency scores under the meta-frontier framework (Table 9).

Table 9. TGR analysis for the two stages.

Stage1			
	1	2	3
2015	0.999	0.899	0.879
2016	0.994	0.850	0.869
2017	0.986	0.885	0.907
2018	1.000	0.904	0.888
2019	0.999	0.865	0.887
2020	1.000	0.886	0.879
Mean	0.998	0.881	0.884
Stage2			
	1	2	3
2015	0.627	0.453	0.637
2016	0.734	0.302	0.587
2017	0.719	0.433	0.747
2018	0.645	0.350	0.599
2019	0.668	0.259	0.554
2020	0.829	0.226	0.369
Mean	0.701	0.338	0.577

Firstly, the technical improvement space in the eastern region in these two stages was 0.02% and 29.91%, respectively. Similarly, for the central region, the technical improvement space in the production stage was 11.86%, while it was as high as 66.21% in the governance stage. The western region had an 11.62% improvement space in the first stage and a 42.31% improvement space in the governance stage. This result indicates that, although there is room for improvement in the production stage, all three regions—eastern, central, and western—need to focus on the governance stage for sustainable water resource development.

From the changes in TGR scores in the governance stage over the six years, we can see that the eastern region's TGR score shows an upward trend. This suggests that the eastern region's technological standards are gradually improving and approaching the benchmark production level. In contrast, for the central and western regions, the TGR scores showed a decline, which may be attributed to a lack of improvement in investment capital and technological conditions or to an unreasonable allocation of inputs.

5. Conclusions and Discussion

This study developed an entropy recycling dynamic two-stage SBM model, wherein energy poverty is incorporated as the exogenous variable, to assess the efficiency of water resource production and governance across 29 provinces in mainland China. There was a significant difference found in the efficiencies of water resource utilization and governance when considering the impact or non-impact of energy poverty as an exogenous variable, thus highlighting the distinct efficiency patterns in the two-stage efficiency as well as the individual input and output indices. The key findings from this study are as follows:

1. In terms of the total efficiency of the sustainable use of water resources, only 4 of the 29 provinces of China have achieved an ideal efficiency, and the other 25 provinces have different degrees of room for improvement. Provinces such as Gansu and Shanxi need greater improvement. There were fluctuating downward trends in 14 of the provinces from 2015 to 2020, with the largest decline in Chongqing. Based on empirical findings, it is evident that the majority of provinces in western China show significant potential for enhancing water resource sustainability efficiency. Furthermore, these provinces demonstrated higher fluctuations in efficiency performance, thereby highlighting the need for heightened attention and proactive measures to bolster governance, as well as the need to elevate overall efficiency levels, thereby ensuring development stability.

2. The efficiency performance in the governance stage was better than that observed in the production stage for most areas among the 29 provinces. There were nine provinces that achieved the desired scores in the production stage, while only five managed this in the governance stage. The worst efficiency performance in both stages was in Shanxi. In most regions, the efficiency of the production stage lagged behind that of the governance stage, thereby suggesting a higher prevalence of production or management issues in the former. A deeper analysis of water resource utilization, production process management, and technological proficiency in the production stage would be advantageous for enhancing efficiency.

3. The efficiency scores of the index at the production stage (S1) were found to be slightly higher than those of the index at the governance stage (S2) for most of the areas.

There are 11 provinces that need improvement in output index efficiency in S1, while 13 of the provinces need substantial efficiency enhancements in S2. The labor efficiency of the provinces performed better than the wastewater treatment one, for which most of the provinces had the worst scores, with only 4 of the provinces achieving the desired efficiencies and 16 of the provinces having an efficiency score of less than 0.6. The average efficiency score of the other 11 provinces was found to be less than 0.3. Moreover, there were 14 provinces that had significantly declining efficiency scores; thus, there is a need for their improvement to keep rising. Between the wastewater index, waste gas index (WGI), and solid waste (SW) indicators, the WGI efficiency generally needed more improvement, particularly in provinces such as Shaanxi, Shanxi, Zhejiang, Anhui, Shanghai, Shandong, Yunnan, and Fujian (whose efficiency values were less than 0.5). The performance for the SW indicator was also relatively poor, with eight provinces showing a great need for improvement. There were better performances in the wastewater index, with seven of the provinces requiring only some room for improvement (though the overall improvement needs for most of the areas were not less). This indicated a favorable trend toward continuous efficiency enhancement. Therefore, analyzing the disparities in the input–output indicator efficiency performance highlighted the need for targeted improvement, primarily in wastewater treatment. Both urban areas in the eastern and western regions require additional intervention and technological investment in this aspect, with a potential emphasis on centralized wastewater treatment.

4. In terms of the TGR, the performance for provinces from the eastern region was found to be better than the ones from the central region during S1, with the central region slightly ahead of the western region. The performance of the provinces in the eastern region maintains its lead in S2. Among the 13 eastern provinces, 7 of them exhibited relatively poor technology levels, with Zhejiang having the lowest on average. Of the provinces from the central region, five out of six provinces demonstrated satisfactory technology levels, with only Jiangxi being slightly below 1. Among the 10 western provinces, 6 of them demonstrated relatively satisfactory technology levels, while the remaining 4 provinces were deficient, with Shaanxi having the lowest technology level. The disparities in technological proficiency revealed significant variations between China's eastern, central, and western regions. While the eastern region leads with respect to the 29 main provinces, the western region lags behind, thereby necessitating tailored interventions to bridge this gap. Additionally, notable technological discrepancies were found to exist within the eastern region itself. Consequently, the policy measures should include macro-level and regionally coordinated development strategies, along with region-specific governance initiatives, to systematically address technological disparities and promote the sustainable development of water resources.

6. Policy Implication

From the above, it can be seen that the efficiency performance of the production stage for 29 provinces in 2020 was greatly affected by the pandemic, thus resulting in a generally huge space for efficiency improvement in most areas. Considering the fact that China has entered the post-pandemic era, the strategy for improving the efficiency of water resource production and governance efficiency should be considered from other dimensions, and targeted and comprehensive measures should be taken to carry out this aim. Specific recommendations are as follows:

Compared to the provinces from the eastern and central regions, the provinces from the western region need more support from sound policies and activities with more proactive measures to leverage their resource advantages and enhance their overall efficiency for water resource production and governance. This involves actively upgrading water resource production and governance through advanced technology. Notably, Gansu and Yunnan, among the 10 provinces, need heightened attention and more effective measures due to their better-than-expected water production and governance efficiency, which have been influenced by energy poverty. Gansu, Shaanxi, and Yunnan have exhibited relatively lower levels of economic growth and social development when compared with the other 10 western provinces. Gansu faces challenges in water resource distribution due to its geographic location and topography, which make production, utilization, and management complex. The region's management practices also lag behind those of other areas. An initial step would involve assessing the current state of water resource utilization and management, conducting an inventory of input factors in water production and management phases, and focusing on human resource development to enhance personnel efficiency and output.

Simultaneously, it is crucial to evaluate the degree of exhaust gas, wastewater treatment, and solid waste disposal fundamentals in order to identify the inefficiencies and proactively address them. Yunnan's governance priorities should center on improving production and management levels during the production phase for exhaust gas, wastewater, and solid waste. Other provinces in the western region should concentrate on continuous improvement and management-level enhancement. In general, learning from the governance experience of high-efficiency eastern regions, adopting advanced management techniques and production technologies, introducing cutting-edge equipment, and promoting technical efficiency improvement are essential goals.

Improving the technological competence of urban areas in the central and western regions can be accomplished through inter-regional technical collaboration, technology transfer, and the recruitment of scientific expertise. This will enhance the management of water resources in these regions. Provinces from the central region, particularly the Shanxi and Henan provinces, have lagged far behind the others in terms of technological efficiency. For the Shanxi province, great attention needs to be directed to both production and governance activities. Challenges in the production stage stem from its high energy and resource dependence. Inadequate production, as well as technology and management levels, can adversely impact water resource efficiency during production. Given that both Shanxi and Henan are major coal production bases in mainland China, addressing water management issues in the coal production industry is crucial. Efficient wastewater, waste gas, and solid waste treatment demand increased government attention and investment, including the introduction of advanced equipment and the promotion of improved technology. Additionally, learning from advanced experiences, emphasizing technical personnel training, and integrating technology in environmental management should be key priorities for future initiatives.

The central government of China should support the western provinces' development by leveraging the economic strengths and social development of the eastern region to encourage regional industry cooperation. This support can be extended to enhance water resource utilization and management in the western regions through technology and experience sharing. While the provinces from the eastern region hold a leading position in terms of economic growth and social development due to their favorable geographical location and historical factors, it is crucial for relatively developed regions like Shanghai, Zhejiang, and Fujian to prioritize governance investment and improvement. In comparison to more highly developed Western countries, mainland China requires more effective technologies and conditions for gas and solid waste management. Learning from the experiences of developed nations, introducing advanced technology and equipment, strategically designing treatment systems for gas and solid waste, attracting technical and management talents, improving management standards, and establishing long-term strategic plans for sustainability are all essential steps. These efforts aim to elevate treatment standards and achieve the Sustainable Development Goals for energy utility and environmental sustainability.

7. Limitations

While we have examined various aspects of water resource sustainability and regional technological efficiency differences between the provinces and cities in China, further analysis of the factors influencing regional disparities can provide more detailed policy recommendations and offer a more comprehensive guide for urban water resource management.

Water resource sustainability presents a multifaceted challenge influenced by geographical, climatic, and socioeconomic factors. This study exclusively utilized data from 29 provinces in China, thus limiting the spatio-temporal scope and potentially hindering a more comprehensive depiction of regional dynamics and temporal trends. Future research could explore the following avenues: Firstly, in the current context, emphasizing climate change and its policy implications may significantly enhance sustainable resource management practices. Secondly, diverse resource endowments across countries and regions could render resource allocation policies non-universal. Consequently, conducting broader and more focused studies is imperative for advancing the Sustainable Development Goals.

Author Contributions: Conceptualization, Y.L. and Y.-H.C.; Methodology, Y.-H.C.; Software, Y.-H.C.; Validation, Y.L.; Formal analysis, Y.L. and L.D.; Investigation, Y.-H.C.; Resources, Y.L. and Y.-H.C.; Data curation, Y.L. and Y.-H.C.; Writing—original draft, L.D. and Y.-H.C.; Writing—review & editing, Y.L. and L.D.; Visualization, L.D.; Supervision, Y.-H.C.; Project administration, Y.L. and Y.-H.C.; Funding acquisition, Y.L. All authors have read and agreed to the published version of the manuscript.

Funding: 71773082: China National Natural Science Fund; H200109: Industry project: Building sustainable organization in industry.

Data Availability Statement: The datasets used and analyzed during the current study are available from the corresponding author on reasonable request. Data recourse is contained within the article.

Conflicts of Interest: The authors of this manuscript have no conflicts of interest to disclose.

References

1. Khalkhali, M.; Dilkina, B.; Mo, W. The role of climate change and decentralization in urban water services: A dynamic energy-water nexus analysis. *Water Res.* **2021**, *207*, 117830. [CrossRef]
2. Li, D.L.; Zuo, Q.T.; Zhang, Z.Z. A new assessment method of sustainable water resources utilization considering fairness-efficiency-security: A case study of 31 provinces and cities in China. *Sustain. Cities Soc.* **2022**, *81*, 13. [CrossRef]
3. UNDESA. *Sustainable Development Goals Report 2018*; UNDESA: New York, NY, USA, 2018.
4. FAO. *AQUASTAT—FAO's Global Information System on Water and Agriculture*; Food and Agriculture Organization of the United Nations (FAO): Rome, Italy, 2021.
5. Lyu, S.; Chen, W.; Zhang, W.; Fan, Y.; Jiao, W. Wastewater reclamation and reuse in China: Opportunities and challenges. *J. Environ. Sci.* **2016**, *39*, 85–96. [CrossRef]
6. Serrao-Neumann, S.; Renouf, M.A.; Morgan, E.; Kenway, S.J.; Choy, D.L. Urban water metabolism information for planning water sensitive city-regions. *Land Use Policy* **2019**, *88*, 104144. [CrossRef]
7. Ke, J.; Khanna, N.; Zhou, N. Analysis of water-energy nexus and trends in support of the sustainable development goals: A study using longitudinal water-energy use data. *J. Clean. Prod.* **2022**, *371*, 12. [CrossRef]
8. IEA (International Energy Agency). *Energy and Poverty, World Energy Outlook 2002*; IEA: Paris, France, 2002.
9. Zhao, J.; Jiang, Q.; Dong, X.; Dong, K. Assessing energy poverty and its effect on CO_2 emissions: The case of China. *Energy Econ.* **2021**, *97*, 15. [CrossRef]
10. Sun, D.Y.; She, J.W.; Liu, L.Y.; Wang, H.M. Efficiency evaluation for industrial water use and analysis of the Spatio-temporal differences in the Yangtze River Delta urban agglomeration. *Resour. Environ. Yangtze Basin* **2018**, *27*, 3–10.
11. Song, M.L.; Tao, W.; Shang, Y.; Zhao, X. Spatiotemporal characteristics and influencing factors of China's urban water resource utilization efficiency from the perspective of sustainable development. *J. Clean. Prod.* **2022**, *338*, 13. [CrossRef]

12. Sun, C.; Zhao, L.; Zou, W.; Zheng, D. Water resource utilization efficiency and spatial spillover effects in China. *Acta Geograph. Sin.* **2014**, *5*, 771–788. [CrossRef]
13. Pereira, M.A.; Marques, R.C. Sustainable water and sanitation for all: Are we there yet? *Water Res.* **2021**, *207*, 11. [CrossRef]
14. Wang, M.; Sun, C.Z.; Wang, X.L. Analysis of the Water-Energy Coupling Efficiency in China: Based on the Three-Stage SBM-DEA Model with Undesirable Outputs. *Water* **2019**, *11*, 632. [CrossRef]
15. Pei, Y.J.; Song, W.W.; Shi, J.W.; Pang, H. Flow field and strength analysis of composite space guide blade structure of inclined flow pump. *Water Resour. Power* **2017**, *6*, 40.
16. Guo, Y.R.; Hu, Y.; Shi, K.; Bilan, Y. Valuation of Water Resource Green Efficiency Based on SBM-TOBIT Panel Model: Case Study from Henan Province, China. *Sustainability* **2020**, *12*, 6944. [CrossRef]
17. Chen, C.Y.; Lin, S.H.; Chou, L.C.; Chen, K.D. A comparative study of production efficiency in coastal region and non-coastal region in Mainland China: An application of metafrontier model. *J. Int. Trade Econ. Dev.* **2018**, *27*, 901–916. [CrossRef]
18. Cai, J.L.; Zhao, D.; Varis, O. Match words with deeds: Curbing water risk with the Sustainable Development Goal 6 index. *J. Clean. Prod.* **2021**, *318*, 14. [CrossRef]
19. Ding, X.H.; He, J.H.; Wang, L.Y. Inter-provincial water resources utilization efficiency and its driving factors considering undesirable outputs. *China Popul. Resour. Environ.* **2018**, *28*, 157–164.
20. Zhang, W.; Wang, D.; Liu, X.M. Does financial agglomeration promote the green efficiency of water resources in China? *Environ. Sci. Pollut. Res.* **2021**, *28*, 56628–56641. [CrossRef]
21. Messerli, P.; Kim, E.M.; Lutz, W.; Moatti, J.-P.; Richardson, K.; Saidam, M.; Smith, D.; Eloundou-Enyegue, P.; Foli, E.; Glassman, A.; et al. Expansion of sustainability science needed for the SDGs. *Nat. Sustain.* **2019**, *2*, 892–894. [CrossRef]
22. Di Vaio, A.; Trujillo, L.; D'Amore, G.; Palladino, R. Water governance models for meeting sustainable development Goals: A structured literature review. *Util. Policy* **2021**, *72*, 23. [CrossRef]
23. Yang, J.; Liu, X.; Ying, L.; Chen, X.; Li, M. Correlation analysis of environmental treatment, sewage treatment and water supply efficiency in China. *Sci. Total Environ.* **2020**, *708*, 8. [CrossRef]
24. Sun, C.; Ma, W. Spatial correlation network of water resources green efficiency between provinces of China. *Geogr. Res.* **2020**, *39*, 53–63.
25. Fu, L.; Xu, Y.; Xu, Z.; Wu, B.; Zhao, D. Tree water-use efficiency and growth dynamics in response to climatic and environmental changes in a temperate forest in Beijing, China. *Environ. Int.* **2020**, *134*, 105209. [CrossRef]
26. Liang, X.D.; Li, J.; Guo, G.; Li, S.; Gong, Q. Urban water resource utilization efficiency based on SBM-undesirable-Gini coefficient-kernel density in Gansu Province, China. *Environ. Dev. Sustain.* **2023**, *25*, 13015–13034. [CrossRef]
27. He, W.J.; Lai, Y.S.; Karmacharya, B.M.; Dai, B.F.; Hao, Y.T.; Xu, D.R. Geographical heterogeneity and inequality of access to improved drinking water supply and sanitation in Nepal. *Int. J. Equity Health* **2018**, *17*, 40. [CrossRef] [PubMed]
28. Liu, H.; Jia, Y.; Niu, C.; Gan, Y. Spatial Pattern Analysis of Regional Water Use Profile Based on the Gini Coefficient and Location Quotient. *J. Am. Water Resour. Assoc.* **2019**, *55*, 1349–1366. [CrossRef]
29. Sharma, P.; Kumar, S.N. The global governance of water, energy, and food nexus: Allocation and access for competing demands. *Int. Environ. Agreem. Polit. Law Econ.* **2020**, *20*, 377–391. [CrossRef]
30. Stojilovska, A.; Zivcic, L.; Barbosa, R.; Grossmann, K.; Guyet, R. *Compendium: On Existing and Missing Links between Energy Poverty and Other Scholarly Debates*; ENGAGER, COST Association: Brussels, Belgium, 2020.
31. Hao, Y.; Hu, X.L.; Chen, H.Y. On the relationship between water use and economic growth in China: New evidence from simultaneous equation model analysis. *J. Clean. Prod.* **2019**, *235*, 953–965. [CrossRef]
32. Xu, W.J.; Zhang, X.; Xu, Q.; Gong, H.; Li, Q.; Liu, B.; Zhang, J. Study on the Coupling Coordination Relationship between Water-Use Efficiency and Economic Development. *Sustainability* **2020**, *12*, 1246. [CrossRef]
33. Du, Y.B.; Tu, Y.; Li, Z.; Nie, L. Regional water resources security grading evaluation considering both visible and virtual water: A case study on Hubei province, China. *Environ. Sci. Pollut. Res.* **2022**, *29*, 25824–25847. [CrossRef]
34. Yao, X.; Feng, W.; Zhang, X.; Wang, W.; Zhang, C.; You, S. Measurement and decomposition of industrial green total factor water efciency in China. *J. Clean. Prod.* **2018**, *198*, 1144–1156. [CrossRef]
35. Liu, J.; Tone, K. A multistage method to measure efficiency and its application to Japanese banking industry. *Socio-Econ. Plan. Sci.* **2008**, *42*, 75–91. [CrossRef]
36. Sueyoshi, T.; Goto, M. Environmental assessment by DEA radial measurement: U. S. coal-fired power plants in ISO (independent system operator) and RTO (regional transmission organization). *Energy Econ.* **2012**, *34*, 663–676. [CrossRef]
37. Zhang, S.J.; Liu, J.; Li, C.; Yu, F.; Jing, L.; Chen, W. Evaluation of Water Resources Utilization Efficiency Based on DEA and AHP under Climate Change. *Water* **2023**, *15*, 718. [CrossRef]
38. Shi, C.F.; Zeng, X.; Yu, Q.; Shen, J.; Li, A. Dynamic evaluation and spatiotemporal evolution of China's industrial water use efficiency considering undesirable output. *Environ. Sci. Pollut. Res.* **2021**, *28*, 20839–20853. [CrossRef] [PubMed]
39. Liu, J.S.; Lu, L.Y.Y.; Lu, W.M. Research fronts in data envelopment analysis. *Omega* **2016**, *58*, 33–45. [CrossRef]
40. Yang, Y. Evaluation of China's water-resource utilization efficiency based on a DEA-Tobit two-stage model. *Water Supply* **2021**, *21*, 1764–1777. [CrossRef]
41. Liang, X.D.; Li, J.; Guo, G.; Li, S.; Gong, Q. Evaluation for water resource system efficiency and influencing factors in western China: A two-stage network DEA-Tobit model. *J. Clean. Prod.* **2021**, *328*, 12. [CrossRef]

42. Xie, Q.W.; Ma, H.; Zheng, X.; Wang, X.; Wang, F.Y. Evaluation and Spatial-Temporal Difference Analysis of Urban Water Resource Utilization Efficiency Based on Two-Stage DEA Model. *IEEE Trans. Comput. Soc. Syst.* **2022**, *9*, 1282–1296. [CrossRef]
43. Tone, K. A slacks-based measure of efficiency in data envelopment analysis. *Eur. J. Oper. Res.* **2001**, *130*, 498–509. [CrossRef]
44. Tone, K.; Tsutsui, M. Network DEA: A Slacks Based Measurement Approach. *Eur. J. Oper. Res.* **2009**, *197*, 243–252. [CrossRef]
45. Tone, K.; Tsutsui, M. Dynamic DEA with network structure: A slacks-based measure approach. *Omega-Int. J. Manag. Sci.* **2014**, *42*, 124–131. [CrossRef]
46. Sun, J.; Li, G.; Wang, Z. Technology heterogeneity and efficiency of China's circular economic systems: A game meta-frontier DEA approach. *Resour. Conserv. Recycl.* **2019**, *146*, 337–347. [CrossRef]
47. Chang, M.C.; Hu, J.L.; Chen, C.H. A metafrontier pollution efficiency analysis of Taiwan's administrative regions. *J. Clean. Prod.* **2019**, *222*, 393–406. [CrossRef]