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Research on the Water Environment Governance of Hangzhou Bay Based on the DEA–Tobit Model

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Abstract: With rapid urbanization and industrialization, Hangzhou Bay faces significant pressure in water environment governance. This study, based on panel data from 2011 to 2021 in Zhejiang's Hangzhou, Jiaxing, Shaoxing, and Ningbo, employs the Super-Efficiency DEA model to assess water environment governance performance. The Tobit model analyzes external environmental factors. Findings reveal fluctuating water governance efficiency during the study period, with inefficiencies from 2012 to 2019, followed by significant improvement from 2019 to 2021. Key factors impacting governance include urban water environment performance in Hangzhou, urban residents' disposable income, population density, and secondary industry GDP development. A higher urban income enhances environmental awareness and governance performance, while population density and industrial GDP intensify resource use, energy consumption, and wastewater discharge, worsening governance pressures and performance. This research offers insights for enhancing water environment governance in Hangzhou Bay, aiding in the formulation of protection plans and management policies. Additionally, it provides valuable experiences for watershed governance globally.

Keywords: DEA–Tobit; Hangzhou Bay; water environment governance; performance evaluation

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1. Introduction

Hangzhou Bay, located in the northeastern part of the Zhejiang Province of China, and being the second largest bay area of the country, serves as a core development area of the Yangtze River Delta. Over the years, due to rapid industrialization, the Hangzhou Bay Economic Zone in particular has been seen to be significantly contributing to the growth in economy, which accounts for about 68% of the total economic output of Zhejiang Province, mainly from 78% of the domestically listed high-tech companies (75% of which are China's top 500 private enterprises). Consequent to these, the area has undergone accelerated urbanization and has witnessed challenges related to them. From amongst many of these challenges, pollution of the Hangzhou Bay waters resulting from a continuous increase in discharge of the domestic waste water and industrial effluents into the Bay due to insufficient wastewater treatment capacity has been a major concern; hence, this has intensified the pressure for water governance in the region [1]. According to the Ecological Environment Condition Reports of Zhejiang Province for the recent years, the water quality in the nearshore waters of the Hangzhou Bay area has remained at Class IV, indicating a "poor" ecological environment state, persistently. In the new era, it is of strategic significance for our region to take measures to ensure water safety, ecological health, and a livable water environment.

Hangzhou Bay extends from the Cao'e River weir section between Ganpu Town in Haiyan County and Shangyu District in the west to the line connecting Yangzi Point and Zhenhai Point in the east, adjacent to the waters of Zhoushan and Beilun Port. It is bordered by Shaoxing City to the west, Ningbo City to the east, and Jiaxing City and Shanghai City to the north. The bay is a trumpet-shaped estuary where the Qiantang River and Cao'e

River converge. The scope of this study includes Hangzhou City, Ningbo City, Shaoxing City, Jiaxing City, and the nearshore waters of the Hangzhou Bay area, extending from Shanghai in the north to Zhoushan in the south and to the mouth of the Qiantang River in the west, as shown in Figure 1.

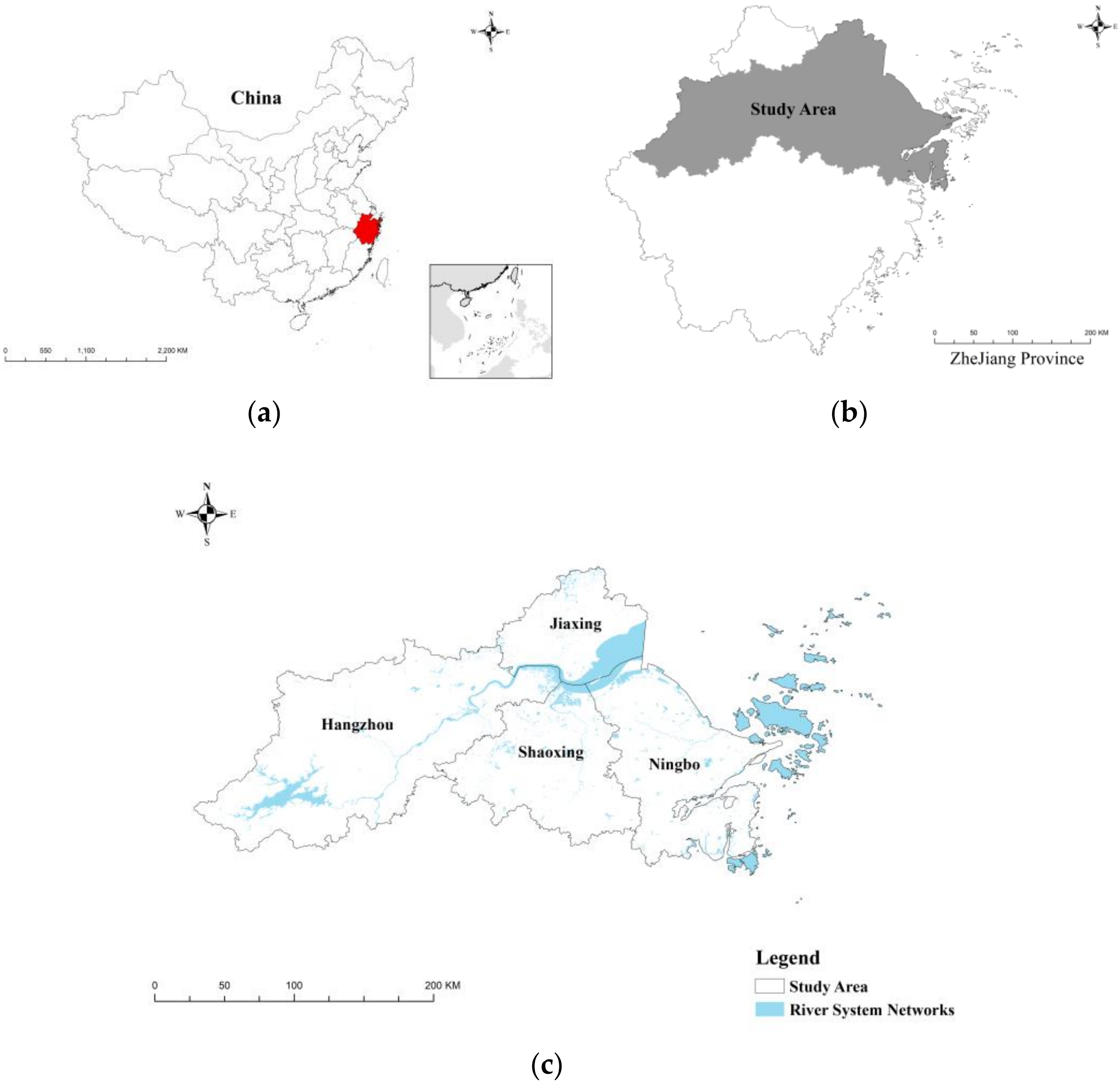

Figure 1. Schematic diagram of the study area delineated in this study. (**a**) The location of Zhejiang Province in China; (**b**) The study area of Zhejinag Province; (**c**) Distribution of river system networks in Hangzhou Bay.

Environmental protection and pollution control have been common challenges faced by countries around the globe in the process of industrialization. Many Western countries encountered severe environmental problems and large-scale pollution incidents during their rapid industrialization in the late 19th century, such as the 1930 Meuse Valley event in Belgium, the 1943 Los Angeles photochemical pollution event in the United States, and the 1986 Rhine River pollution incident [2,3]. Rachel Carson's book "Silent Spring" in 1962 highlighted the widespread pollution and ecological damage caused by overindustrialization, triggering a broader understanding of the conflicts between economic development and environmental protection. The concept of sustainable development was subsequently introduced in the 1972 report by the Club of Rome titled "Limits to Growth". It emphasized the need for shared responsibility in managing the contradiction between environmental degradation and economic progress. Recognizing the importance of water environment governance, the Chinese government has implemented various measures to address the challenges in the Hangzhou Bay area. Initiatives such as the "Zhejiang Coastal Waters Pollution Prevention and Control Plan" and the "Hangzhou Bay Regional Pollution Comprehensive Treatment Plan" were introduced in 2013. Subsequently, the "Zhejiang Marine Environmental Pollution Special Treatment Work Plan" was implemented in 2016. In 2019, the "Hangzhou Bay Pollution Comprehensive Treatment Campaign Implementation Plan" was launched, aiming to address ecological and environmental issues and support the development of a world-class modern bay area in the Zhejiang Province [4]. In 2022, the "Key Waters Comprehensive Treatment Campaign Action Plan" was introduced, focusing on Hangzhou Bay, coastal cities, and their management waters. The plan aims to control pollution sources, improve water quality in nearshore areas, protect estuarine habitats, and promote the high-level protection of the marine ecological environment, thereby facilitating the integrated development of the Yangtze River Delta region [5]. Therefore, it is very important to analyze the performance of Hangzhou Bay water management and its influencing factors.

In this study, the performance evaluation of water environment governance is approached from the perspective of the DEA–Tobit model. It comprehensively considers multiple input–output variables to measure governance efficiency and takes into account various external factors such as socio-economic factors, industrial development, and population density. The aim is to determine the causal relationship between the water governance performance in the Hangzhou Bay area and these influencing factors in order to reflect the long-term impacts of water environment governance on socio-economic and resource development within the region. Our workflow is illustrated in Figure 1. This study focuses on the assessment of water environmental governance performance in the Hangzhou Bay region. Firstly, we collected water environmental governance data such as the expenditure on agricultural, forestry, and water affairs and the sewage treatment rate from 2011 to 2021 in the region. Then, we utilized the Super-Efficiency data envelopment analysis (SE-DEA) model combined with the Tobit model to evaluate the performance of the region in water environmental governance. Finally, based on the research findings, we developed an innovative model for water environmental governance using the Triple Helix theory and proposed recommendations for optimizing water environmental governance.

The rest of this paper is organized in the following way. Section 2 reviews the related literature. Section 3 describes the data and methodology in detail. Section 4 presents the results and discussion. Section 5 provides the main conclusions.

2. Literature Review

The evaluation of water environmental governance performance, as an important tool in environmental management, originated from the United States with the passage of the Clean Water Act in 1972 [6], which marked the beginning of efforts to protect and manage water bodies. This act established regulations for the management and limitation of water quality, making the evaluation of water environmental governance performance a necessary task. Subsequently, in 1990, the U.S. Environmental Protection Agency developed the Total Maximum Daily Load (TMDL) program, which was further supported by related rules published in 1992 [7]. This program established water quality goals and assessed the improvement of water quality through monitoring, modeling, and analysis, thus becoming an important method for evaluating water environmental governance performance. During the same period, the European Union began formulating the Water Framework Directive, which stipulated comprehensive management and protection measures for water bodies [8]. The directive required member states to classify and assess water bodies within their territories and set water quality objectives and deadlines, and became an important standard for evaluating water environmental governance performance. Since then, the evaluation of water environmental governance performance has been incorporated into systematic research, yielding substantial results over the past few decades.

The research on water environment governance performance includes the construction of indicator systems, evaluation of various subsystems of water environment governance, analysis of driving forces, and their applications. In terms of research methods for water environment performance assessment, many domestic and international scholars and research institutions, after understanding the theoretical mechanisms of the water environment's impact on socio-economic dynamics, analyze water quality through real-time monitoring, mathematical modeling, and physical and chemical analysis to assess the governance performance of water environments. The research methods have evolved from index evaluation methods to the current data envelopment analysis [9], analytic hierarchy process [10], and artificial neural networks [11], and the research scope has expanded from the performance evaluation of individual water treatment plants to regional and watershed water environment governance performance. Lassaux used the Life Cycle Analysis (LCA) method to calculate the effluent water quality of 100 sewage treatment plants and measure their governance performance using indicators such as treatment efficiency and lime consumption [12]. Hernández et al. evaluated the sewage treatment efficiency of 338 sewage treatment plants in Spain using the data envelopment analysis (DEA) method, with energy expenditure, maintenance costs, labor costs as input variables, and the pollution treatment rate as the output variable. They found that most sewage treatment plants had a low governance efficiency, and subsequently analyzed the obstacles causing the low governance efficiency [13]. Zaheer and Bai (2003) proposed a new artificial neural network based on the decision-making method for water quality management to control environmental pollution, which was used to assess the relative impact of various pollution sources on river water quality [14]. Guo et al. used the SBM–Tobit method to construct an assessment model to calculate the green efficiency of water resources in 18 cities in Henan Province from 2011 to 2018, discussed the operational mechanisms of relevant influencing factors, and identified methods to improve the green efficiency of water resources [15]. Alodah et al. simulated hydrological impacts of extreme events by generating random climate data to conduct research on water resource system risks and performance [16]. Regarding the construction of model indicator systems, Pires et al. constructed 170 water management indicators from three dimensions—environment, economy, and society—to measure the sustainable development of water resource utilization [17]. Rak et al. (2019) proposed a comprehensive risk assessment method for self-managed water supply systems that takes into account multiple factors such as frequency or probability, property loss, health impacts, and safety. They developed a four-parameter risk matrix that enables a comprehensive evaluation of the risk level in water supply systems. The method was validated through case studies and demonstrated good practicality in small- and medium-sized water supply systems [18]. Urbanik et al. (2019) employed a multi-parameter risk matrix approach to assess pipeline failure risks in natural gas supply systems. This method comprehensively considers factors such as pipeline type, failure probability, and consequence effects. A risk matrix was developed to evaluate the risks, and the effectiveness of the method was validated through case studies [19]. Li et al. (2016) established an evaluation index system for water security using five subsystems—water cycle security, water environmental security, water ecological security, water social security, and water economic security with 39 indicators—and used macroeconomic data from 2000 to 2012 to assess the water security status of China using a water security evaluation model [20].

In terms of research on strategies for water environment pollution control, different countries have different governance models and strategies due to the relationship between water governance and sustainable socio-economic development. As environmental protection efforts started earlier in foreign countries compared to domestic ones, the governance models and strategies established by them have a greater reference value for water governance in China [21,22]. The US government initiated the protection and governance of the Mississippi River in the 1960s, maintaining a stable ecological environment in the surrounding river basin. The main focus was on establishing mechanisms for public participation, integrating ecological environmental protection with economic development, and rational resource allocation, progressing from point source management to non-point source management [23]. Due to the rapid economic growth in Japan after World War II, the pressure on the water environment carrying capacity in the Lake Biwa region increased, leading to severe pollution and declining water quality [24]. The Japanese government established a government-led and citizen-participatory protection mechanism for the Lake Biwa basin [25]. The management shifted from extensive management to a combination of development and utilization with ecological protection. This is related to the background that many countries have proposed Integrated Water Resources Management (IWRM) since the 1990s [26,27]. IWRM presents a framework for comprehensive water resources management, constructing interactions among natural water resource systems, human activity systems, and water resource management systems. It emphasizes the interactions between water resource systems and human activities, and emphasizes the coordination between water resource utilization and ecological environmental protection [28].

In summary, the existing literature on the evaluation of water environment governance performance has several limitations. Firstly, although there have been studies on the evaluation of water environment governance performance in different countries or regions, there is a lack of research focusing on the Hangzhou Bay area, resulting in insufficient findings. Secondly, the measurement methods used for evaluating water environment performance often involve subjective factors. For example, the determination of indicator weights using methods like the Delphi method and analytic hierarchy process (AHP) may not objectively reflect the facts. In light of these limitations, this study adopts the widely used objective evaluation method of data envelopment analysis (DEA) and extends the original model by incorporating the Super-Efficiency DEA (SE-DEA) method. It considers both positive and negative indicators and utilizes actual water environment data from the Hangzhou Bay area over the past decade to construct an evaluation system for water environment governance performance. The SE-DEA–Tobit model is employed to assess the effectiveness of regional water environment governance and identify potential external influencing factors during the governance process. This research aims to provide reference and recommendations for the scientific formulation of water environment protection plans and management policies. The findings can also serve as valuable insights for watershed governance in other countries and regions.

3. Materials and Methods

3.1. Data Acquisition

Based on the background of rapid industrialization and urbanization in the Hangzhou Bay area, this study establishes an SE-DEA–Tobit model to address the water environment governance issues in the region. Panel data from 2011 to 2021 are selected to assess the performance of water environment governance in Hangzhou Bay, aiming to identify directions and breakthrough points for improving the performance level in future water environment governance efforts.

The data used in this study mainly include socioeconomic data, environmental protection data, and water environment governance data of the four cities in the Hangzhou Bay area and the adjacent coastal waters. The data sources include the Zhejiang Statistical Yearbook, Hangzhou Statistical Yearbook, Jiaxing Statistical Yearbook, Shaoxing Statistical Yearbook, and Ningbo Statistical Yearbook for the years 2012–2022. Additionally, data from the Zhejiang Environmental Bulletin, Ningbo Environmental Status Bulletin, Hangzhou Environmental Status Bulletin, Jiaxing Environmental Status Bulletin, Shaoxing Environmental Status Bulletin, as well as a small portion of other data from official websites of relevant departments and news reports, were utilized.

3.2. Data Processing and Description

In the Taihu Lake region, the water environmental governance situation exhibited fluctuations during the study period, but overall showed an improving trend. To address the issue of dimensional influence in the data, we performed the following normalization procedure:

$$x' = \frac{x - \min(x)}{\max(x) - \min(x)} \quad (1)$$

where x represents each column of our data, we conducted normalization by subtracting the minimum value from each column over the period of 2011–2021 and then dividing it by the difference between the maximum and minimum values across all years. This normalization process was performed to eliminate the dimensional influence. The descriptive statistics of all variables are presented in Table 1.

Table 1. Descriptive statistics of variables.

Variables	Mean	Sd	Median	Min	Max	Skew	Kurtosis
Expenditure on agricultural, forestry, and water affairs	490,475.30	162,828.87	573,581.33	230,820.67	685,440.67	454,620	−0.43
Sewage treatment rate	0.93	0.03	0.93	0.88	0.98	0.1	0.03
Length of drainage pipelines	6614.05	1754.29	6033.26	4467.92	10,101.53	5633.61	0.49
COD emissions from industrial wastewater	18,366.82	9046.64	15,112.45	8185.26	30,765.25	22,579.99	0.14
Total amount of industrial wastewater discharge	27,642.36	18,142.13	22,072.09	17,011.40	81,176.53	64,165.13	2.28
Rate of water quality compliance	0.81	0.15	0.81	0.59	1.00	0.41	−0.11
Urban per capita disposable income	51,826.61	12,971.84	50,744.00	33,229.00	72,877.25	39,648.25	0.13
Number of patents granted	35,134.14	12,066.31	30,520.25	20,338.00	62,682.00	42,344	1.04
Area of nearshore waters classified as Grade IV (worst category)	0.78	0.33	1.00	0.21	1.00	0.79	−0.80

Between 2011 and 2021, the overall investment in water environmental governance has increased over time, as shown in Figure 2. For example, the investment in agricultural, forestry, and water affairs showed a gradual increase from 2011 to 2015. It remained stable from 2016 to 2018 and reached its maximum value in 2019. However, it decreased to 79.01% in 2021. The indicator of sewage treatment rate exhibited a consistent increase from 2011 to 2021, reaching its maximum value of 100% in 2020 and 2021. As for the variable of drainage pipeline, it demonstrated a year-by-year increase from 2011 to 2019 but experienced a decline in 2020 due to the replacement of aging pipelines with new ones. It reached its peak in 2021 after the successful replacement process.

When it comes to the overall performance related to water environmental governance, there are some improvements in the effectiveness of water environment management over time, as shown in Figure 3. Specifically, the total industrial wastewater discharge exhibited a consistent decrease from 2011 to 2021. It declined from 100% in 2011 to 18.89% in 2012, and continued to decrease steadily to 1.21% in 2021. The trend in chemical oxygen demand (COD) emissions from industrial wastewater followed a similar pattern, with a relatively slow decline from 2011 to 2015, followed by a rapid decrease from 2016 to 2018, indicating significant achievements in water environmental governance. On the other hand, the water quality compliance rate showed a gradual increase from 2011 to 2021, with a stable trend in recent years.

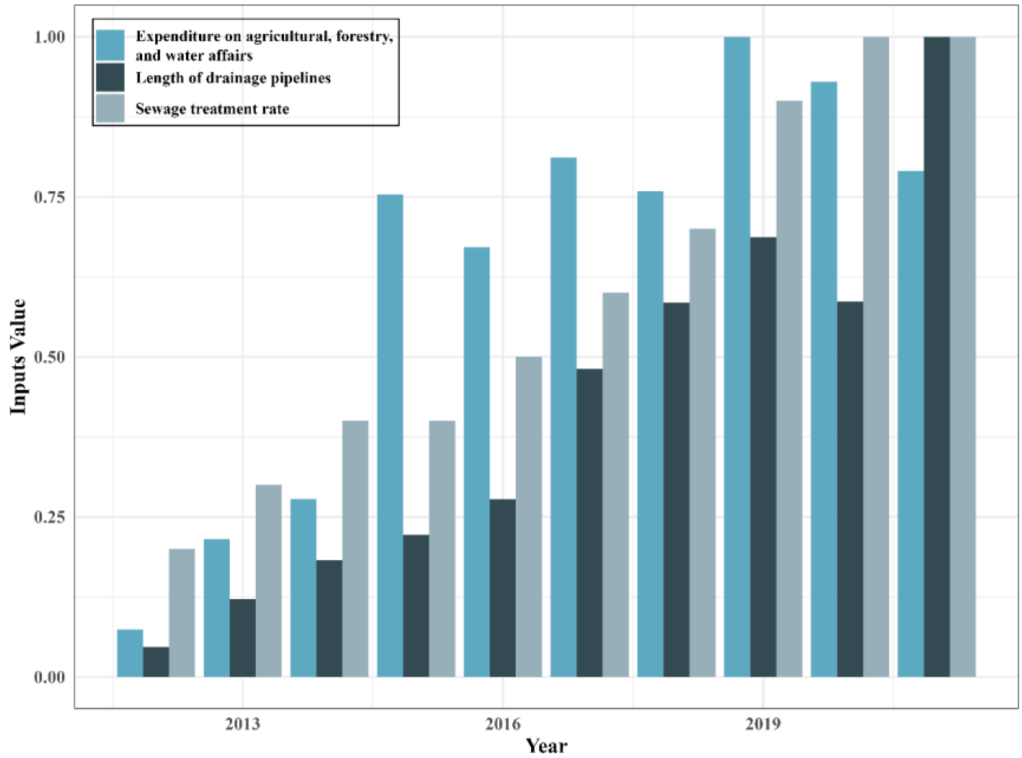

Figure 2. Inputs change between 2011 and 2021.

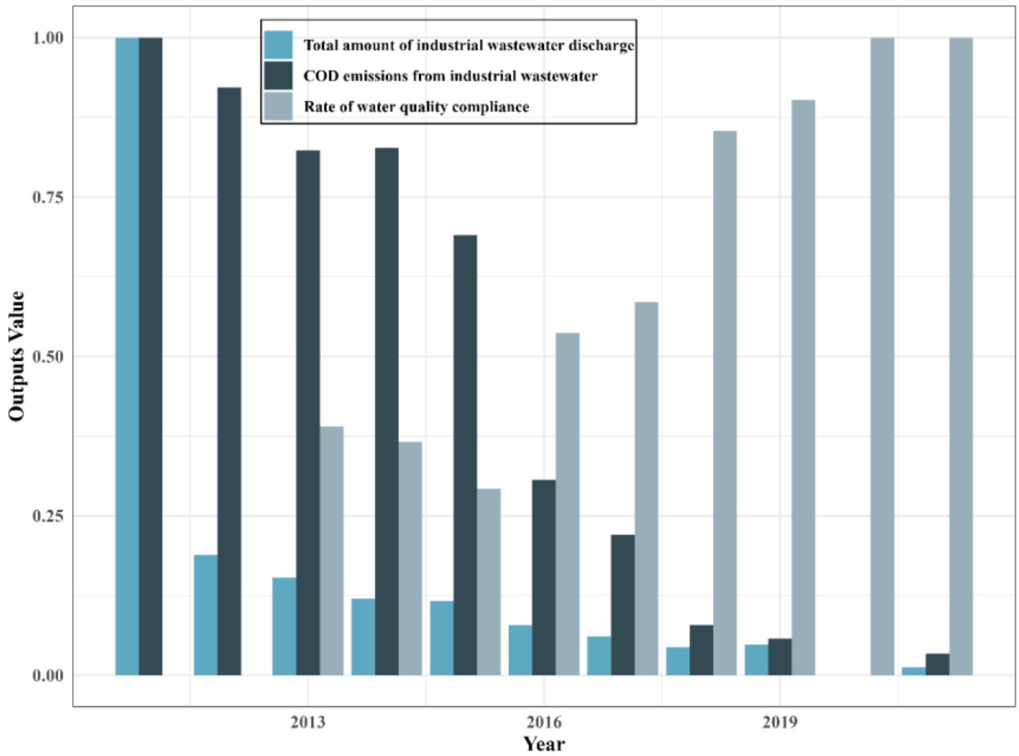

Figure 3. Outputs change between 2011 and 2021.

3.3. Model Construction

3.3.1. Super-Efficiency DEA Model

The Super-Efficiency DEA model is an improved version of the traditional DEA (data envelopment analysis) model, which allows for a more accurate assessment of the efficiency of decision-making units (DMUs) and provides more discriminative efficiency evaluation results [29,30].

Traditional DEA models typically only identify the efficient frontier for each DMU but cannot determine the optimal efficient frontier [31]. This means that even if a DMU is on the efficient frontier, there may be other DMUs that can better utilize the same resources and technology, thus achieving higher efficiency. The Super-Efficiency DEA model introduces the concept of super-efficiency to determine the optimal efficient frontier and provide a more accurate assessment of each DMU's efficiency [32].

The core of the Super-Efficiency DEA model is that for each DMU, there exists a super-efficient point above the optimal efficient frontier, indicating that the DMU's resource utilization and technological efficiency can be further improved. By comparing the difference between the super-efficient point and the actual efficiency, the relative efficiency and ranking of each DMU can be determined [33].

The model construction is shown as follows:

$$Minimize : \theta_k - \varepsilon\left(\sum_{i=1}^{m} s_i^- + \sum_{r=1}^{s} s_r^+\right) \tag{2}$$

$$s.t.\begin{cases} \sum\limits_{j=1}^{n} \lambda_j x_{ij} + s_i^- = \theta_k x_{ik},\ i = 1,\cdots,m, j \neq k \\ \sum\limits_{j=1}^{n} \lambda_j y_{rj} - s_r^- = \theta_k y_{rk},\ r = 1,\cdots,s, j \neq k \\ \lambda_j,\ s_i^+,\ s_r^- \geq 0 \end{cases} \tag{3}$$

where n represents the number of DMUs (decision-making units), m represents the number of input variables, s represents the number of output variables, x_{ij} represents the value of the i-th input variable for the j-th DMU, y_{rj} represents the value of the r-th output variable for the j-th DMU, θ_k represents the super-efficiency value of the k-th DMU, λ_j represents the weight coefficient, and ε is a non-Archimedean element defined as a value smaller than any positive real number, used to avoid zero weights.

The specific indicator system is divided based on the SE-DEA model, as shown in Table 2. In the input layer, we selected three representative indicators of water environmental inputs, including the expenditure on agricultural, forestry, and water affairs in fiscal expenditure, sewage treatment rate, and the length of drainage pipelines [34]. In the output layer, we selected representative indicators of governance outcomes, such as the rate of water quality compliance to measure the efficiency of sewage treatment, and the total amount of industrial wastewater discharge to assess the improvement in governance standards [35]. Due to the negative nature of the indicators of industrial wastewater discharge and COD (chemical oxygen demand) emissions in the output layer, we employed the approach commonly used in the literature, which incorporates negative indicators into the input layer for modeling purposes [36,37].

Table 2. The evaluation index system based on the DEA model.

Phase	Input/Output	Indicator	Serial Number
Water Environment Governance	Input	Expenditure on agricultural, forestry, and water affairs (in 10,000 yuan)	X1
		Sewage treatment rate (%)	X2
		Length of drainage pipelines (in km)	X3
	Output	Rate of water quality compliance (%)	Y1
		Total amount of industrial wastewater discharge (in 10,000 tons)	Y2
		COD (chemical oxygen demand) emissions from industrial wastewater (in tons)	Y3

3.3.2. Tobit Model

The water environmental governance performance in the Huantaihu region, as measured by the Super-Efficiency DEA model, is not only influenced by input–output indicators but also by various external factors. Therefore, it is necessary to assess the impact of these external factors on the efficiency of water governance [38]. In this study, the truncated regression Tobit model is employed to analyze the influencing factors of water environmental governance performance in the Huantaihu region.

The Tobit model is a regression analysis model used to handle data with lower or upper censoring limits. In such cases, the values of the dependent variable are restricted by observed lower or upper limits, which can cause ordinary linear regression models to estimate inaccurately [39]. The Tobit model was initially proposed by economist James Tobin in 1958 for analyzing household expenditure data. And it has now been widely applied in various fields, including social sciences, medical research, and market surveys [40].

When using the DEA method to measure water environmental governance performance, there may be one or more decision variables on the efficiency frontier, leading to a possible truncation of efficiency values. Multiple decision variables may become censored. Conventional regression equations cannot explain the attribute differences between extreme and non-extreme values in the case of truncated data, resulting in biased parameter estimates [39].

Therefore, in this study the Tobit model is employed to analyze the factors influencing the efficiency of water environmental governance in the Huantaihu region. This will help identify the key factors affecting water governance efficiency and provide sufficient empirical data for subsequent policy recommendations. The development of this model is presented as follows:

$$y_t = \begin{cases} \alpha_t + \beta^T X_t + \mu_t, & y_t > 0 \\ 0 \quad , & y_t \leq 0 \end{cases} \tag{4}$$

$$\mu_{i,t} \sim N(0, \sigma^2) \tag{5}$$

The dependent variable, y_t, represents the water environmental governance efficiency in the Hangzhou Bay area in year t. The explanatory variable, X_t, represents the external factors influencing water environmental governance and is taken as the actual observed values. The parameter to be estimated is denoted as β^T. When the dependent variable $y_t \leq 0$, the observed value is truncated at 0, and when the dependent variable $y_t \geq 0$, the actual observed value is taken.

In the Tobit model, the dependent variable is the water governance efficiency value obtained from the SE-DEA model in Hangzhou Bay. The explanatory variables include the DEA efficiency values of water governance performance in Hangzhou and Ningbo, urban per capita disposable income (UPDI), and the number of patents granted (NPG). The control variables include GDP, secondary industry GDP, and total population, as shown in Table 3 [41].

Table 3. The evaluation index system based on the Tobit model.

Input/Output	Indicator	Serial Number
dependent variable	Hangzhou Bay DEA Efficiency Score	Score1
explanatory variables	Hangzhou DEA Efficiency Score	Score2
	Ningbo DEA Efficiency Score	Score3
	urban per capita disposable income	UPDI
	number of patents granted	NPG
control variables	GDP	GDP
	secondary industry GDP	SIGDP
	total population	TP

We propose the following three hypotheses to be tested using the Tobit model:

Hypothesis 1: *The better the water environmental governance performance in Hangzhou and Ningbo cities, the better the overall water environmental governance performance in the Hangzhou Bay area. The water environmental governance performance in Hangzhou and Ningbo cities is also represented by the efficiency values obtained from the SE-DEA model.*

Hypothesis 2: *A higher urban per capita disposable income indicates a better awareness of water environmental protection among urban residents and a more effective water environmental governance in cities, leading to higher DEA efficiency values in the Hangzhou Bay area.*

Hypothesis 3: *A higher number of patents granted indicates more active research and development (R&D) activities, resulting in the development of patents and new products that are beneficial for water environmental governance. This contributes to an improvement in water environmental governance efficiency in the Hangzhou Bay area.*

4. Results

4.1. Analysis of SE-DEA Model Results

From the above model, we obtained the efficiency values and rankings of the SE-DEA model. Based on the respective indicator data of the coastal cities Hangzhou and Ningbo, we calculated the DEA efficiency values and rankings for each city, as shown in Table 4.

Table 4. DEA Efficiency Score and rank.

Time (DMUs)	Hangzhou Bay		Hangzhou		Ningbo	
	Eff.Score	Rank	Eff.Score	Rank	Eff.Score	Rank
2011	1.12	2	1.16	2	0.88	8
2012	0.97	9	0.99	8	1.15	3
2013	1.09	3	1.04	5	0.90	7
2014	0.97	7	0.85	11	0.79	10
2015	0.88	11	0.94	10	0.71	11
2016	1.00	6	1.13	3	0.93	5
2017	0.89	10	0.96	9	0.85	9
2018	1.01	5	1.01	6	0.92	6
2019	0.97	8	1.00	7	0.94	4
2020	1.17	1	1.12	4	1.33	2
2021	1.07	4	1.28	1	1.39	1

From Figure 4, it can be observed that the DEA Efficiency Score of Hangzhou Bay exhibits frequent fluctuations. Specifically, the water environmental governance efficiency in the Hangzhou Bay region decreased from 1.12 in 2011 to 1.07 in 2021. Among these years, the efficiency values equal to or greater than one were observed in 2011, 2013, 2018, 2020, and 2021, indicating that these years achieved effective governance efficiency, where the inputs for water environmental governance were effectively transformed into improvements in the water environment. However, in the remaining years, the DEA efficiency values were below one, indicating inefficient governance. This suggests that the inputs for water environmental governance were not fully translated into improved outputs. From a trend perspective, the years with efficiency values below one were concentrated in the period of 2014–2019, with only 2018 surpassing 1.01 in efficiency. This indicates that the water environmental governance efficiency in Hangzhou Bay was relatively low during this period, with potential redundancies in input, particularly in agricultural, forestry, and water affairs expenditures. Additionally, although the length of drainage pipelines increased year by year, there was no significant improvement in wastewater treatment. From the output perspective, the water quality compliance rate decreased annually from 2013 to 2015, and the changes in wastewater discharge and COD emissions were not significant from 2014 to 2019. This suggests that the conversion from input to output was not effective during these periods.

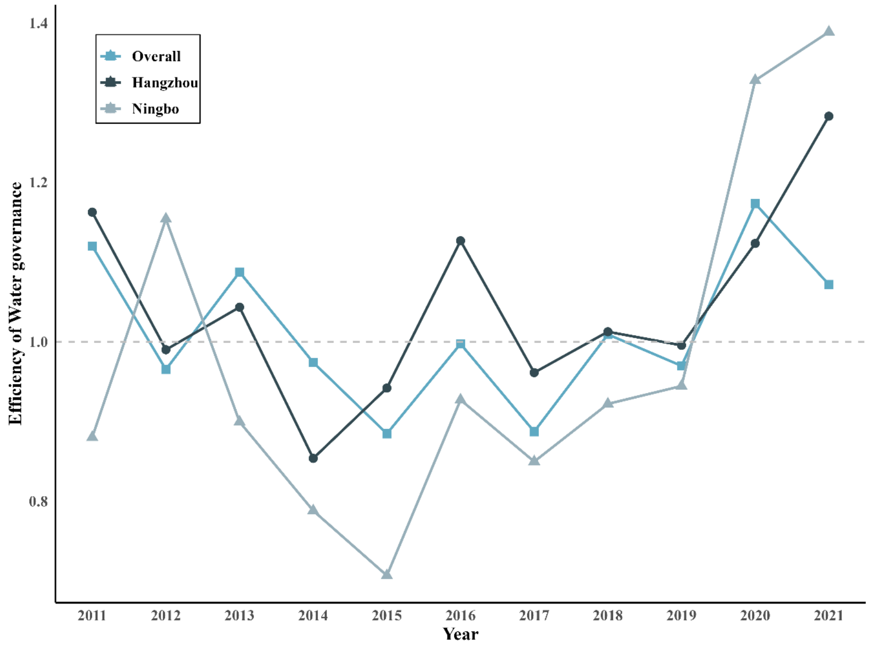

Figure 4. DEA Efficiency Scores of Hangzhou Bay and Coastal Cities from 2011 to 2021.

From Figure 4, it can be observed that the DEA Efficiency Score of Hangzhou exhibits an overall "W"-shaped trend. It decreased during 2011–2014 and 2016–2017, and increased during 2014–2016 and 2019–2021. Specifically, the water environmental governance efficiency in Hangzhou increased from 1.16 in 2011 to 1.28 in 2021. During the study period, the years with DEA efficiency values equal to or greater than one were 2011, 2013, 2016, 2018, 2020, and 2021, indicating effective water environmental governance in these years, while the remaining years showed inefficient governance. In terms of trends, there were clear downward trends during 2011–2014 and 2016–2017, while upward trends were observed during 2014–2016 and 2019–2021. This indicates that the water environmental governance in Hangzhou experienced fluctuations during the period of 2011–2019, with frequent declines in governance efficiency. Although there were improvements in 2014, 2015, and 2016, the high-efficiency performance level could not be sustained. However, the water environmental governance efficiency significantly improved after 2019, with a considerable increase, indicating a significant improvement in governance performance.

From Figure 4, it can be observed that the DEA Efficiency Score of Ningbo exhibits an overall trend of first increasing, then decreasing, and then increasing again. It increased during 2011–2012 and 2015–2021, and decreased during 2012–2015. Specifically, the water environmental governance efficiency in Ningbo increased from 0.88 in 2011 to 1.39 in 2021. During the study period, only the years 2012, 2020, and 2021 had DEA efficiency values greater than one, indicating effective governance in these years, while the remaining years had values less than one, indicating poor governance efficiency and significant redundancy in water environmental governance investment. From 2013 to 2019, Ningbo's water environmental governance remained in an inefficient state for a total of seven years. This can be attributed to the significant challenges in water pollution control itself, as well as the presence of substantial non-essential expenses in governance investment. It suggests that the same outputs can be achieved with reduced investment.

4.2. Analysis of Tobit Model Results

The regression results of this study were obtained through R programming. The estimation results are shown in Table 5.

Table 5. Tobit regression results.

Time (DMUs)	Estimate	Std.Error	z-Value
Intercept	31.94 **	11.30	2.83
Score2	1.02 ***	0.23	4.42
Score3	−0.01	0.13	−0.078
ln(TP)	−6.90 **	2.36	−2.92
ln(UPDI)	3.17 *	1.27	2.50
ln(NPG)	0.11	0.13	0.82
ln(GPD)	−1.45	1.03	−1.41
ln(SGDP)	−1.29 ***	0.36	−3.61
ln(Scale)	−3.24 ***	0.21	−15.22

Notes: * Significant at the 10% level, ** significant at the 5% level, and *** significant at the 1% level.

From Table 3, it can be observed that both the DEA Efficiency Score2 for water environmental governance in Hangzhou and the significance level of the secondary industry GDP are below 0.1%. The significance level of the total population is below 1%, while the significance level of urban residents' disposable income is 5%. This indicates that these variables have significant effects on water environmental governance in the Hangzhou Bay area. The results confirmed hypotheses 1 and 2, but not hypothesis 3. It is noteworthy that the coefficient for the DEA efficiency variable of Hangzhou city is 1.02, while the coefficient for urban residents' disposable income is 3.17. This suggests that the water environmental governance efficiency in the Hangzhou Bay area is primarily influenced by Hangzhou city's water environmental governance efficiency. Additionally, an increase in urban residents' disposable income promotes people's attention to environmental quality. With higher incomes, people tend to prioritize their living quality and health, leading to an increased emphasis on water environmental governance and improvement [38]. Moreover, an increase in urban residents' disposable income can generate more fiscal revenue for the government, enabling it to allocate more funds to water environmental governance. Therefore, the government can utilize these funds to enhance water environmental infrastructure, strengthen monitoring and management, and improve water pollution control technologies and equipment. Furthermore, the increase in urban residents' disposable income can also promote the awareness and sense of responsibility for environmental protection among enterprises and residents, encouraging them to actively participate in water environmental governance and enhance its effectiveness.

From the perspective of control variables, the control variables selected in this study include GDP, secondary industry GDP, and the total population. The results indicate that the total amount of secondary industry GDP has a significant impact on the DEA efficiency value of the Hangzhou Bay area at a 99.9% confidence level, while the total population variable has a significant impact on performance level at a 99% confidence level. Moreover, the coefficients for both variables are negative, with a coefficient of −1.29 for the secondary industry GDP and −6.90 for the total population. This indicates that the growth of the secondary industry is usually accompanied by increased energy consumption and pollution emissions. Manufacturing processes in the industry often require significant amounts of energy and raw materials, leading to the generation of wastewater, exhaust gases, and solid waste, which can directly or indirectly have a negative impact on water environments. Additionally, it may result in excessive exploitation and utilization of water resources, increased water demand for industrial development, and potential issues such as water depletion, declining water levels, and deteriorating water quality, thereby affecting water environmental governance and protection. Furthermore, the development of the secondary industry may lead to lax environmental management. As evident from the performance analysis, during the study period from 2012 to 2019, both in the Hangzhou Bay area and Hangzhou and Ningbo cities, water environmental governance performance remained ineffective. This indicates that, in order to promote economic growth, the government may lower environmental requirements and regulatory efforts for enterprises, adopting extensive management methods, which reduce the control and governance capabilities of enterprises regarding environmental pollution and subsequently affect the effectiveness of water environmental governance.

On the other hand, an increase in the total population also leads to a decline in water environmental governance performance and an increase in governance pressure. Firstly, population growth can result in excessive exploitation of water resources. With an increase in population, the demand for water resources also rises. If water resources are improperly developed and utilized, it can lead to issues such as water depletion, declining water levels, and deteriorating water quality, thereby affecting water environmental governance and protection. Secondly, population growth contributes to increased water pollution. Urbanization and industrialization accompanying population growth intensify the degree of water pollution. For instance, densely populated cities and industrial areas often generate a significant amount of wastewater, exhaust gases, and solid waste, which can directly or indirectly impact water environments negatively [42]. Thirdly, population growth poses challenges to environmental management. As the population increases, the government needs to allocate more resources and efforts to manage and protect the water environment. However, in practice, the difficulty of environmental management and governance increases with population growth, as it involves dealing with more pollution sources and governance targets.

5. Discussion

(1) Collaborative governance among government, industry, academia, and research can enhance governance performance.

This study combines the actual situation of water environmental governance in Hangzhou Bay and analyzes the periodic fluctuations in governance performance through the DEA–Tobit model. It is found that relying solely on the government as the single governance entity is no longer sufficient to address governance pressures. Therefore, introducing collaborative efforts among government, industry, and the public can effectively enhance governance performance. On the one hand, the government should allocate reasonable financial budgets for water governance through "visible hands" and impose production constraints on highly polluting companies through corresponding laws and policies. On the other hand, as the key subject of water governance, the industry's production activities directly affect water quality and governance effectiveness. So, the industry should upgrade outdated industries and reduce pollution in accordance with policies while improving water efficiency through the constantly improving water rights market. At the same time, the public should participate in governance through collaborative efforts among government, industry, academia, and research, which can significantly optimize governance effectiveness. As direct beneficiaries of water governance, the public can improve their sense of satisfaction and sense of acquisition.

(2) Strengthen sewage treatment and reduce emissions.

Efforts should be made to achieve a standardized governance of industrial point source pollution, increase environmental protection requirements, strictly control new sources of pollution, accelerate the ecological management of non-point sources (especially agricultural sources), control agricultural pollution, reduce the use of fertilizers and pesticides, promote organic and ecological agriculture, and accelerate the construction of various sizes of sewage treatment plants to comprehensively strengthen watershed sewage treatment. At the same time, multiple approaches should be used to treat existing pollution and increase the water environmental capacity. Continuing to implement cross-basin large-scale water diversion measures can promote the flow and exchange of water bodies in various lake areas, reduce inferior water sources from small- and medium-sized rivers entering the lake, and improve the water environment. The introduction of high-tech water environmental governance such as source pollution control systems, artificial aeration systems, and submerged plant purification systems can effectively improve the water quality of lakes in conjunction with traditional technologies such as ecological dredging and blue-green algae harvesting. New sewage treatment technologies such as biofilm reactors and MBR should be promoted to improve sewage treatment efficiency and quality. In addition, diversified sewage treatment technologies such as using wetlands, artificial infiltration, and groundwater replenishment can be utilized through natural processes, and strategies such as rainwater collection and separate discharge can be used to achieve rain and sewage separation and reduce pollutant emissions.

(3) Optimize industrial structure to achieve clean production.

From the government's perspective, a comprehensive industrial adjustment plan should be formulated with clear goals and a roadmap for optimizing the industrial structure. This includes developing guidance principles for clean production, identifying priority areas for clean industrial development, and formulating corresponding policy support measures. The plan should consider national development needs, resource endowments, and environmental capacity, and rationally guide industrial development. At the same time, the government can provide financial and economic support to clean production enterprises through fiscal and tax policies. This includes reducing the tax burden of enterprises, providing subsidies for clean technology research and development, and establishing green credit funds.

For enterprises, existing industrial structures should be adjusted, and clean production should be promoted comprehensively to guide industries towards low pollution and low energy consumption. Outdated production capacity should be phased out, and high-tech reforms should be introduced to reduce pollution emissions in the production process. Water resource waste and losses caused by crude water supply methods should be reduced, which can improve production efficiency and reduce pollution treatment costs.

(4) Promote cost-sharing for water environmental governance and achieve water environmental governance transformation through multi-party collaboration.

To change the government's single-handed management model, ecological protection, environmental governance, and monetary compensation should be balanced to provide a reasonable cost-sharing mechanism for water environmental governance. Responsibility and benefit-sharing should be emphasized, with enterprises bearing the costs of water resource use and pollution discharge while consumers support the long-term costs of water environmental governance. A sewage treatment cost-sharing mechanism should be implemented, and the government can establish a special sewage treatment fund to finance the construction, renovation, and maintenance of sewage treatment facilities. Funds can be raised through government appropriations, environmental taxes, sewage discharge fees, etc., to ensure the sustainable development of sewage treatment work. Companies and residents should be charged a certain sewage discharge fee based on their discharge volume and pollutant concentration, and differentiated charges should be implemented for different industries and residents. The fees collected should be used for the construction and operation management of sewage treatment facilities.

To encourage enterprises and residents to actively participate in sewage treatment and emission reduction work, the government can establish a reward and punishment system. Enterprises and residents that meet or exceed emission standards can be rewarded, such as by reducing sewage discharge fees, enjoying tax benefits, or obtaining environmental certification. Enterprises and residents that exceed emission standards or refuse to cooperate should be punished, including fines, production and business suspensions, and revocation of licenses. To ensure the effective implementation of the sewage treatment cost-sharing mechanism, the government should strengthen the supervision and enforcement of sewage discharge enterprises and residents. A monitoring system should be established to regularly sample and test sewage discharge and publicly disclose monitoring results. At the same time, law enforcement efforts should be strengthened to punish enterprises and individuals that violate emission standards and sewage treatment cost-sharing mechanisms, ensuring the effectiveness of the system.

6. Conclusions and Limitations

6.1. Conclusions

This article addresses the issue of water environmental governance in the context of rapid urbanization and industrialization in the Hangzhou Bay area. To measure governance performance, a SE-DEA model was established, and panel data from 2011 to 2021 were used to calculate the governance efficiency of the Hangzhou Bay region and the coastal cities of Hangzhou and Ningbo. Based on the actual development situation in the region, the reasons for changes in the water environmental governance performance of the Hangzhou Bay region, Hangzhou, and Ningbo were analyzed separately. Using the efficiency values obtained from the SE-DEA model as the dependent variable, a Tobit model was used to analyze the impact of external factors on governance efficiency and to infer causality for factors other than input–output in water environmental governance. This provides a starting point and breakthrough for comprehensively improving the governance efficiency of the Hangzhou Bay area's water environment.

During the study period, the governance performance of the Hangzhou Bay region exhibited frequent fluctuations, with the water environmental governance performance often being ineffective from 2012 to 2019. This was mainly due to the rapid socio-economic development of the Hangzhou Bay region during this time, which increased the pressure on water environmental governance. At the same time, the extensive management methods used meant that water environmental governance efficiency remained consistently poor. However, from 2019 to 2021 the water environmental governance performance in the Hangzhou Bay region improved significantly, with the DEA efficiency value increasing from 0.97 to 1.17, shifting from an ineffective state to a super-efficient state. This reflects a significant improvement in governance effectiveness, with the area of severely polluted waters decreasing from 47.00% to 23.80%, and the water quality compliance rate increasing from 92.50% to 98.80%. From the perspective of urban water governance, the water environmental governance efficiency of Hangzhou and Ningbo cities exhibited a "W-shaped" trend, indicating poor governance from 2012 to 2019, but significant improvement in recent years.

Using the Tobit model to analyze the external factors influencing water environmental governance, it was found that hypothesis 1 was partially verified, with the main breakthrough point for improving the governance efficiency of the Hangzhou Bay region's water environment being the urban water environmental governance level in Hangzhou city. Hypothesis 2 was also correct, as an increase in disposable income for urban residents leads to greater environmental awareness and public environmental protection efforts, which is favorable for water environmental governance. Simultaneously, an increase in disposable income can significantly increase fiscal revenue and investment in governance facilities and supervision. Hypothesis 3 was incorrect, as the number of patent authorizations was not significant, due to the contradiction in the transformation of scientific research results in the Hangzhou Bay region's R&D activities, with many patent achievements failing to be successfully transformed into innovative investments in water environmental governance. Furthermore, the control variables revealed that the total population and the GDP of the secondary industry have significant impacts on the water governance performance of the Hangzhou Bay region. On the one hand, an increase in population leads to a higher population density, rapid urbanization, and industrialization, which increases the pressure on governance. On the other hand, the rapid development of the secondary industry leads to increased energy consumption and pollution emissions, exacerbating the deterioration of the water environmental ecology.

6.2. Limitations and Future Directions

The limitations of this study are primarily attributed to the relatively small sample size, as it only covers data from 2011 to 2021. Due to the dynamic nature of water environmental governance, a shorter time span may not fully reflect long-term trends and changes. Therefore, future research on water environmental governance in the Hangzhou Bay area could consider expanding the time range by including data from additional years to obtain more comprehensive and accurate analytical results. Furthermore, although this study focuses on water environmental governance in the Hangzhou Bay area, it lacks consideration of other potential influencing factors or variables. Future research can further broaden the scope of investigation by incorporating factors such as water resource utilization, economic development level, and government policies to obtain more comprehensive and holistic research conclusions.

Lastly, while this study provides initial insights into water environmental governance in the Hangzhou Bay area, there are still unresolved issues and challenges. For instance, questions remain regarding the balance between economic development and ecological/environmental protection, as well as the formulation of effective policies and management measures. Future research can delve deeper into these issues and propose specific solutions to promote the sustainable development of water environmental governance in the Hangzhou Bay area. In summary, by expanding the sample size, extending the time range, considering more influencing factors, and addressing practical challenges, future research can further enhance and advance the field of water environmental governance in the Hangzhou Bay area. This will provide policymakers and decision-makers with more targeted and feasible recommendations to achieve sustainable management and protection of the region's water environment.

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