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A Successful Approach of the First Ecological Compensation Demonstration for Crossing Provinces of Downstream and Upstream in China

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Received: 10 June 2020; Accepted: 24 July 2020; Published: 27 July 2020



Abstract: As the first pilot provincial water environmental compensation set up at the national level, the Xin'anjiang River Basin plays a very important exemplary and guiding role in the ecological compensation of transboundary basins in China. There is no paper evaluating the environmental performance in watershed scale after getting rid of the natural factor's effect. Here we issue a new approach to evaluate it, combing the SPAtially Referenced Regression On Watershed attributes (SPARROW) models and data envelopment analysis (DEA) method, based on counterfactual scenarios. After ecological compensation, the results show that the decrease of total nitrogen (TN) non-point source export coefficient was stable (17.16–17.78% in different sources), while that of total phosphorus (TP; 8.51–17.75%) and permanganate index (COD_{Mn}; 13.10–21.41%) was not. The projects of fertilizer application's effects were relatively obvious; on average, the decreases of the export coefficients were 17.16%, 17.75%, and 21.41% in TN, TP, and COD_{Mn} models, respectively, showing the importance of eco-compensation regulation, not only in non-point source pollution reduction but also resulting in high levels of eco-compensation efficiencies, especially in scale efficiencies. By assessing parameter and modeling uncertainty with the use of the generalized likelihood uncertainty estimation (GLUE) method, the models' structure well represents the hydrological behavior. This study also provides policymakers with a new perspective in accurately measuring the impact of environmental performance, to guide the next step of environmental investment optimization.

Keywords: ecological compensation; environmental investment efficiency; SPARROW model; DEA method; counterfactual scenarios

1. Introduction

High-quality development will replace fast growth as a fundamental economic development target for China [1]. China was gradually entering the new normal of economic growth [2–4], under which the economic structure would be optimized and effects would far exceed those environmental regulations and policies [5]. After decades of rapid economic development, water quality problems have become constraints for green development in China [6]. To address devastating water environmental crises and to improve the quality of economic developments, China has already implemented multiple

regional and national policies [7–9]. It is important to find suitable environmental water management methods to adapt to China's economic conditions and the administrative system. China's existing water management system is managed in accordance with administrative regions instead of river basins [10]. Ecological compensation is an important type of design and institutional arrangements coordinate regional development and ecological environment [11,12]. Ecological compensation in China has improved with the progress of environmental protection [13,14], making the definition close to the new concept of Payment for Ecosystem Services (PES) [15]. However, the practice of river basin ecological compensation in China mostly exists within the jurisdiction of one province, and the practice across provinces with more complicated relations is rare.

After eight years of preparations, in 2012 the Ministry of Finance and the Ministry of Environmental Protection (renamed Ministry of Ecological Environment in 2018) in China formally launched the first demonstration project to address upstream-downstream ecological compensation across provinces in Xin'anjiang River Basin (XRB), which is of great guiding significance for China [16]. XRB, located at the junction of Zhejiang province and Anhui province (Figure 1), is the largest inflow river of the Qiantangjiang River system and Qiandao Lake in Zhejiang province. XRB and Qiandao Lake are not only important drinking water sources of Zhejiang and Anhui provinces [17] but also ecological security barriers of the Yangtze River Delta region [16].

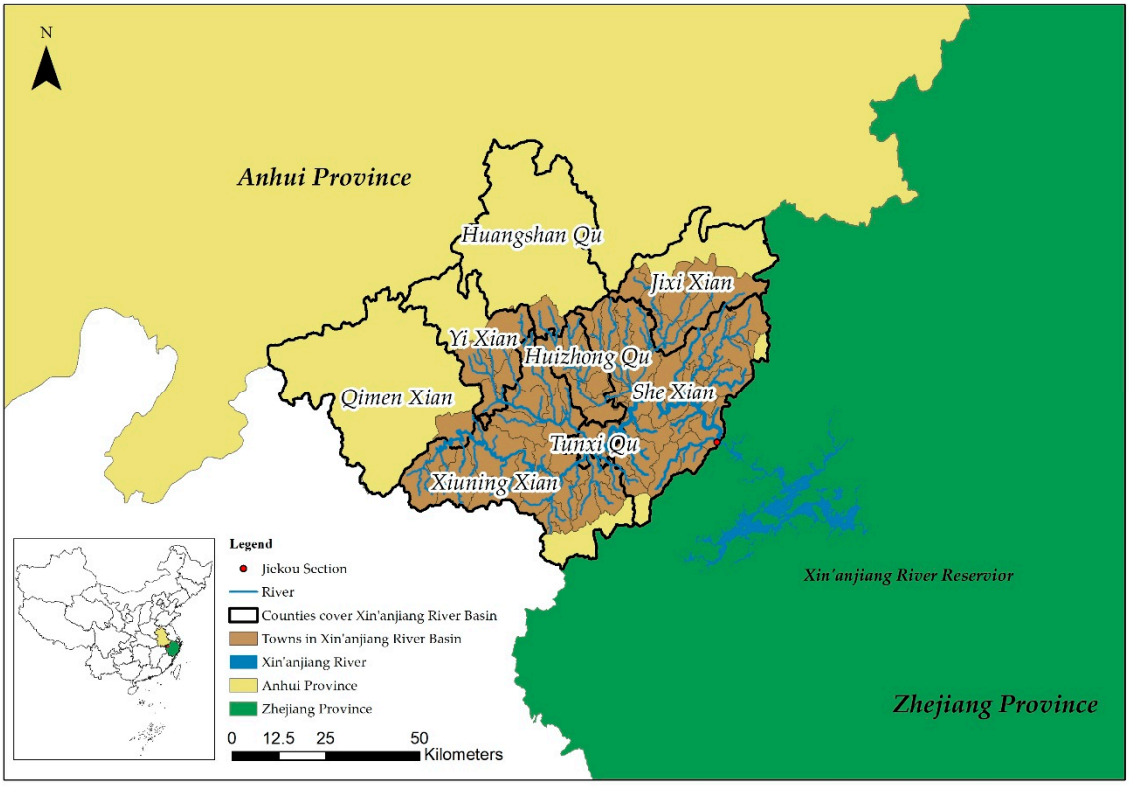


Figure 1. Location of the Xin'anjiang River Basin.

Environmental protection has always been taken seriously in the XRB. The proportions of environmental protection input to financial expenditure in China and XRB are listed in Figure 2 since 2007 [18], which was the year that environmental protection spending began to take into fiscal spending in China. Data are collected from the Ministry of Finance of China and the Bureau of Finance in Huangshan City and Jixi County, which contain the XRB. Although in 2007, the proportions in XRB were greater than those in China. The financial expenditure had significant differences ($p < 0.05$) before and after 2012, which was the year that ecological compensation began. Thus, we take the period of 2012–2017 as consideration of ecological compensation effects.

This project was divided into two stages from 2012 to 2017: first-round stage (2012–2014, XAJ1) and second-round stage (2015–2017, XAJ2), with the total spending of 146.32 hundred million Yuan (Figure S1). With a guaranteed system, diversified funds, and reasonable basis of compensation (see Supplementary Information for details), the mode in XRB was successfully demonstrated, guaranteeing the water quality of downstream. A sufficient preliminary investigation was made to determine the main direction of compensation funds. Each stage summarizes the achievements of each stage. The system ensures that the compensation funds are specifically used for the industrial structure adjustment and industrial layout optimization of the XRB, comprehensive river basin management, water environment protection, water pollution control, and ecological protection. The corresponding projects (Table 1) include sewage treatment, garbage disposal, pesticide and chemical fertilizer treatment, livestock and poultry management, and comprehensive measures.

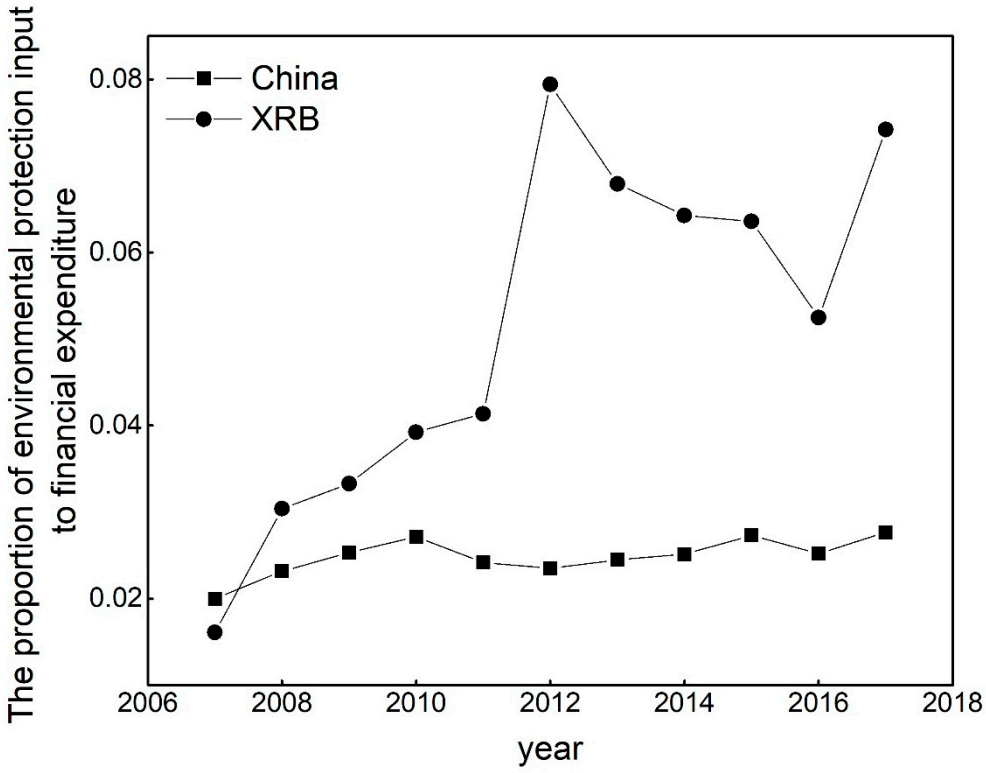


Figure 2. The proportion of environmental protection input to financial expenditure in China and the Xin'anjiang River Basin (XRB).

Table 1. The apportionment of funds for specific ecological compensation projects. XAJ1: first-round stage; XAJ2: second-round stage.

Period	Sewage Treatment	Garbage Disposal	Pesticide and Chemical Fertilizer Treatment	Livestock and Poultry Management	Comprehensive Measures
XAJ1	15.80%	6.76%	1.10%	74.38%	1.96%
XAJ2	8.45%	13.70%	1.65%	73.09%	1.36%
2012–2017	12.23%	10.32%	1.39%	74.39%	1.67%

Identifying precisely how much environmental improvement was due to the compensation funds and whether the funds had been effectively used in different counties is important to evaluate the ecological compensation policy, and is crucial information for decision-makers, particularly in the new normal of China's economy. We chose XRB as our study area not only because the standard of compensation is based on its water quality, but also because the compensation funds were all used to improve the water quality in the period of 2012–2017, which is typical for calculating the environmental performance. The environmental effects were evaluated through a historical trend (2007–2011) analysis of water quality loads to estimate the counterfactual (without ecological compensation) loads in the period of ecological compensation (2012–2017). Yet so far existing studies have focused on the standard mechanism of the ecological compensation [14,19]. Other research has examined the efficiency of payment of ecosystem services [20–22]. However, there are no adequate analyses of the river basin ecological compensation performances with getting rid of the natural conditions' influences.

This article aims to bridge this gap by innovatively using data envelopment analysis (DEA), which uses different kinds of environmental investments as input and counterfactual SPAtially Referenced Regression On Watershed attributes (SPARROW) model results in the watershed as output, to evaluate the environmental investments' efficiency in different counties in the XRB. This approach should be generalizable to different areas and thus valuable beyond the immediate application. The next sections provide (1) a brief introduction of the data sources, the DEA method and SPARROW model and their applications in models, (2) a detailed analysis of each result, and (3) a discussion about the references of the successful approach of the first ecological compensation demonstration for crossing provinces of downstream and upstream in China. To our knowledge, this is the first use of counterfactual scenarios to estimate the environmental performances and related efficiencies in the valuation of ecological compensation. Influences of social and political impacts are beyond the scope of this piece of work due to the lack of data and related researches.

2. Materials and Methods

2.1. Data Sources

Precipitation data were provided in 48 precipitation data sites in the XRB. Water quality data were collected monthly at 60 sites. Flux data used to calibrate the curve numbers were provided by the Environmental Protection Bureau of Huangshan City and Jixi County. Fertilizers and pesticide data were both taken from Anhui statistic yearbook (2007–2017) and provided by XRB Environmental Protection Bureau. The population data were obtained from the government statistical agency website.

2.2. SPARROW Models

The SPARROW water-quality model is a nonlinear least-squares multiple regression model to estimate pollutant sources and tracks the sources of the contaminants [23,24]. This model has been already used successfully in the XRB [17]. To better illustrate the effect of ecological compensation, we chose different sources and water-soil variables to adapt the ecological compensation projects. The SPARROW model easily calculates the delivery loads to the target section (Jiekou Section is the target section we considered in this case, which is also the joint of Anhui province and Zhejiang province, see Figure 1), which makes it quite suitable for Chinese water quality management [25]. The models are based on a detailed stream reach network with 304 sub-catchments delineated from 30-km digital elevation models (DEMs), using ArcHydro [26] extension in ArcGIS. Mean annual water yields were calculated using the Soil Conservation Service (SCS) curve number (CN) method [27].

The structures of SPARROW models are limited to the quantity of the water quality monitor sites [28]. After testing several SPARROW models' structures, we simulated the mean annual flux of total nitrogen (TN), total phosphorus (TP), and permanganate index (COD_{Mn}) in streams as functions of four sources, three climatic and landscape factors that influence pollutant delivery to streams, and pollutant removal in streams (there is no reservoir in this case). Pollutant sources

contain industrial point sources, agricultural plantation sources, livestock and poultry raising sources, and domestic pollution sources. Industrial point sources are the sources of industrial wastewater discharge. Agricultural plantation sources include commercial fertilizer in TN and TP models while including pesticides in COD_{Mn} models. Additionally, we dealt with the population data as the same methods as in the previous study [17] to represent domestic pollution sources.

Measurements of nutrient water quality at stream monitoring sites collected during 2007–2017 were used to develop observations of mean annual nitrogen load as the response variable in the SPARROW regression equations. The mean annual load was estimated as the product of daily streamflow and estimated daily concentration, which was modeled from nutrient water-quality data and streamflow data. We calculated the flux as the same method of the previous study [17].

According to the best model results, the model estimates pollutant delivery to streams, including slope, temperature, precipitation in TN models, and COD_{Mn} models. In TP models, the pollutant delivery parameters are slope, drainage density, and precipitation.

2.3. Counterfactual Scenarios Accounting

The year 2012 is a time node of great significance (Figure 2); the counterfactual scenario assumes no eco-compensation happened. In this scenario, the mean results of 2007–2011 would be used in the coefficient of industrial point sources. All the coefficients of non-point sources, including agricultural plantations sources, livestock and poultry raising sources, and domestic pollution sources, would be influenced greatly by the precipitation. Thus, the improved export coefficient model (IECM) [29] is used to calculate the export coefficients under the situation of the period 2012–2017 if no eco-compensation happened. The IECM is expressed as:

$$L = \sum_{i=1}^{n} \alpha\beta E_i[A_i(I_i)] + p \quad (1)$$

where L is loss of nutrients (kg); Ei is the export coefficient for nutrient source i (kg/ca·yr or kg/km^2·yr); Ai is area of the catchment occupied by land use type i (km^2), or number of livestock type i, or of people; Ii is the input of nutrients to source i (kg); p is the input of nutrients from precipitation (kg); α is the precipitation impact factor; β is the terrain impact factor.

The differences between the actual and counterfactual TN, TP, and COD_{Mn} loads would be considered as environmental performances, which removed the influences of precipitation.

2.4. DEA Method

DEA is a technique to measure efficiency that uses a set of comparable decision-making units (DMUs), calculating the efficient frontier and identify benchmarks [30]. Limited by the lack of data and related research, here we only used the basic input-oriented DEA model, which is used to measure environmental investments' efficiency.

We chose the inflation-adjusted ecological compensation funds as input, and environmental performances as output to calculate technique efficiencies, pure technique efficiencies, and scale efficiencies in different towns to get more DMUs, fitting the model well. Additionally, we used the mean value of the results in different counties, which was the smallest unit that accepted the funds in this case.

2.5. Generalized Likelihood Uncertainty Estimation (GLUE) Method

The GLUE method is extensively used in global sensitivity and uncertainty analysis [31–35], due to the simplicity and applicability to nonlinear systems [31]. Compared to other methods, GLUE is easy to implement. By sampling the prior parameter space using an adaptive Markov Chain Monte Carlo (MCMC) scheme, the computational efficiency of GLUE is improved [36,37]. We used GLUE method in this study to make Monte Carlo sampling from a feasible parameter space with uniform distribution, calculating the likelihood values of behavioral parameter sets. The Nash–Sutcliffe efficiency (ME) was chosen as the likelihood function.

$$\mathrm{ME} = 1 - \frac{\sum (Q_{obs} - Q_{sim})}{\sum \left(Q_{obs} - \overline{Q}_{obs}\right)} = 1 - \frac{\sigma_i^2}{\sigma_{obs}^2} \quad (2)$$

where $\overline{Q}_{obs}$ represents mean values of observed streamflows; σ_i^2 is the error variance for the ith model; σ_{obs}^2 is the variance of observations.

3. Results

3.1. Estimations of SPARROW Models Parameters

Tables 2–4 display the values of parameters in SPARROW TN models, TP models, and COD_{Mn} models. The parameters of industrial point sources represent the proportion of loads delivered to the river; the ranges of coefficients in TN models, TP models, and COD_{Mn} models are 0.871–1.122, 0.741–1.257, and 0.405–0.623, respectively. The reason that some parameters of industrial point sources are greater than 1 may be caused by the uncertainty of the original data.

The parameters in agricultural plantation sources of TN and TP models represent the fertilizer loss coefficient, while the parameters represent the pesticide loss coefficient in the COD_{Mn} models. The ranges of agricultural plantation sources' coefficients in TN models, TP models, and COD_{Mn} models are 0.164–0.266, 0.009–0.016, and 0.166–0.299, respectively, within the range of estimates obtained in the previous study [38].

The parameters in livestock and poultry raising sources represent the pollutants producing coefficients of the pig equivalent in the models. The ranges of livestock and poultry raising sources' coefficients in TN models, TP models, and COD_{Mn} models are 3.373–5.516 kg/yr·capita, 0.495–0.847 kg/yr·capita, and 7.300–13.159 kg/yr·capita, respectively, within the range of estimates obtained in the previous study [38].

The parameters in domestic pollution sources represent the pollutants producing coefficients of the population in the models. The ranges of domestic pollution sources' coefficients in TN models, TP models, and COD_{Mn} models are 1.445–2.775 kg/yr·capita, 0.013–0.023 kg/yr·capita, and 5.849–8.482 kg/yr·capita, respectively, within the range of estimates obtained in the previous study [38].

Tables S1–S3 display the p-values of SPARROW models parameters estimation. There are 99 parameters in each group of SPARROW models. There are 87, 92, and 94 parameter estimations that lie in the 99% confidence interval in SPARROW TN models, TP models, and COD_{Mn} models, respectively.

Table 2. SPARROW total nitrogen (TN) model coefficients calibrated on 60 stations in XRB models.

		2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017
Pollution sources	Point sources	0.871	0.871	0.889	0.927	1.091	1.122	0.921	0.962	0.950	0.883	0.945
	Fertilizer application	0.190	0.225	0.230	0.252	0.214	0.257	0.201	0.206	0.259	0.266	0.164
	Livestock and poultry raising sources	3.777	4.605	4.879	5.149	4.495	5.516	4.119	4.258	5.049	5.487	3.373
	Domestic pollution sources	1.576	2.035	2.203	2.229	2.091	2.775	1.783	1.832	2.293	2.374	1.445
Land delivery factor	Slope	−0.016	−0.015	−0.014	−0.015	−0.014	−0.015	−0.013	−0.014	−0.014	−0.015	−0.013
	Precipitation	0.003	0.005	0.004	0.004	0.003	0.008	0.004	0.007	0.007	0.005	0.003
	Temperature	0.002	0.001	0.002	0.001	0.003	0.005	0.001	0.004	0.004	0.001	0.001
Water delivery factor	k_1	0.159	0.141	0.157	0.144	0.167	0.124	0.139	0.124	0.173	0.162	0.163
	k_2	0.033	0.029	0.031	0.029	0.034	0.036	0.028	0.023	0.026	0.033	0.033

Table 3. SPARROW total phosphorous (TP) model coefficients calibrated on 60 stations in XRB models.

		2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017
Pollution sources	Point sources	0.884	1.011	0.888	1.024	0.897	0.741	0.800	0.868	1.257	0.766	1.171
	Fertilizer application	0.009	0.011	0.012	0.013	0.011	0.014	0.010	0.012	0.014	0.016	0.011
	Livestock and poultry raising sources	0.495	0.622	0.638	0.686	0.600	0.748	0.557	0.680	0.785	0.847	0.584
	Domestic pollution sources	0.013	0.016	0.017	0.018	0.016	0.020	0.015	0.018	0.021	0.023	0.015
Land delivery factor	Precipitation	0.004	0.003	0.004	0.003	0.004	0.003	0.004	0.004	0.003	0.003	0.003
	Slope	−0.027	−0.025	−0.025	−0.025	−0.025	−0.029	−0.025	−0.026	−0.028	−0.053	−0.033
	Drainage density	0.000	0.001	0.000	0.000	0.000	0.005	−0.001	0.001	0.004	0.030	0.011
Water delivery factor	k_1	0.251	0.324	0.313	0.320	0.333	0.297	0.297	0.299	0.287	0.270	0.314
	k_2	0.039	0.051	0.049	0.050	0.052	0.046	0.046	0.047	0.045	0.042	0.049

Table 4. SPARROW permanganate index (COD_{Mn}) coefficients calibrated on 60 stations in XRB models.

		2007	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**
Pollution sources	Point sources	0.541	0.511	0.422	0.567	0.509	0.623	0.602	0.550	0.405	0.523	0.508
	Fertilizer application	2.142	2.473	2.535	2.706	2.361	2.830	2.192	2.336	2.848	2.991	1.657
	Livestock and poultry raising sources	9.368	10.715	11.409	11.897	10.490	12.622	9.607	10.241	12.558	13.159	7.300
	Domestic pollution sources	5.849	6.895	6.929	7.619	6.585	7.809	5.949	6.421	7.929	8.482	7.025
Land delivery factor	Precipitation	0.003	0.007	0.005	0.003	0.005	0.004	0.004	0.003	0.005	0.004	0.003
	Slope	−0.061	−0.064	−0.064	−0.064	−0.064	−0.064	−0.065	−0.064	−0.064	−0.064	−0.064
	Temperature	0.004	0.004	0.005	0.007	0.004	0.007	0.003	0.004	0.003	0.005	0.007
Water delivery factor	k_1	0.943	0.915	0.965	0.937	0.944	0.970	0.901	0.951	0.953	0.927	0.314
	k_2	0.125	0.123	0.132	0.124	0.126	0.132	0.123	0.127	0.128	0.127	0.114

Pollution source apportionment can help in identifying non-point sources as the main pollution sources in XRB. The average source shares of TN loads (industrial point sources/agricultural plantations sources/livestock and poultry raising sources/domestic pollution sources = 1.59/35.90/46.01/16.51) indicated that livestock and poultry raising sources were the predominant nitrogen source (Table 5). After ecological compensation, the proportion of industrial point sources decreased significantly. The reduction of nutrients from point sources in the XRB is important because the effect had instant results.

Table 5. TN loads source apportionment.

Period	Industrial Point Sources	Agricultural Plantations Sources	Livestock and Poultry Raising Sources	Domestic Pollution Sources
2007–2012	2.78%	36.58%	43.81%	16.83%
XAJ1	0.52%	35.84%	47.10%	16.54%
XAJ2	0.62%	34.77%	48.69%	15.92%
2007–2017	1.59%	35.90%	46.01%	16.51%

The source shares of TP loads (industrial point sources/agricultural plantations sources/livestock and poultry raising sources/domestic pollution sources = 0.04/2.60/95.27/2.09) also indicated that livestock and poultry raising sources contributed most (Table 6). Point sources of TP could be negligible.

Table 6. TP loads source apportionment.

Period	Industrial Point Sources	Agricultural Plantations Sources	Livestock and Poultry Raising Sources	Domestic Pollution Sources
2007–2012	0.06%	2.58%	95.11%	2.25%
XAJ1	0.02%	2.68%	95.25%	2.06%
XAJ2	0.02%	2.55%	95.51%	1.92%
2007–2017	0.04%	2.60%	95.27%	2.09%

The source shares of COD_{Mn} loads (industrial point sources/agricultural plantations sources/livestock and poultry raising sources/domestic pollution sources = 1.99/26.37/42.72/28.92) are listed in Table 7. After ecological compensation, the proportion of livestock and poultry raising sources decreased significantly.

Table 7. COD_{Mn} loads source apportionment.

Period	Industrial Point Sources	Agricultural Plantations Sources	Livestock and Poultry Raising Sources	Domestic Pollution Sources
2007–2012	1.68%	26.68%	45.97%	25.67%
XAJ1	5.82%	33.48%	26.03%	34.67%
XAJ2	3.00%	19.97%	21.07%	5.96%
2007–2017	1.99%	26.37%	42.72%	28.92%

3.2. Changes in Export Coefficient

We define the difference between export coefficients of non-point sources in counterfactual scenarios and realistic situations as the decrease in export coefficient after ecological compensation. The results (Figure 3) determine the perspective of environmental performances.

In general, the decrease of non-point source in XAJ2 was better than that in XAJ1, especially in the last year, environmental performance may be delayed after the implementation of the project. The decrease of TN non-point source export coefficients was stable (17.16–17.78% in different sources), while TP (8.51–17.75%) and COD_{Mn} (13.10–21.41%) were not. The projects of fertilizer application's effects were relatively obvious; on average, the decreases of the export coefficients were 17.16%, 17.75%, and 21.41% in TN, TP, and COD_{Mn} models, respectively.

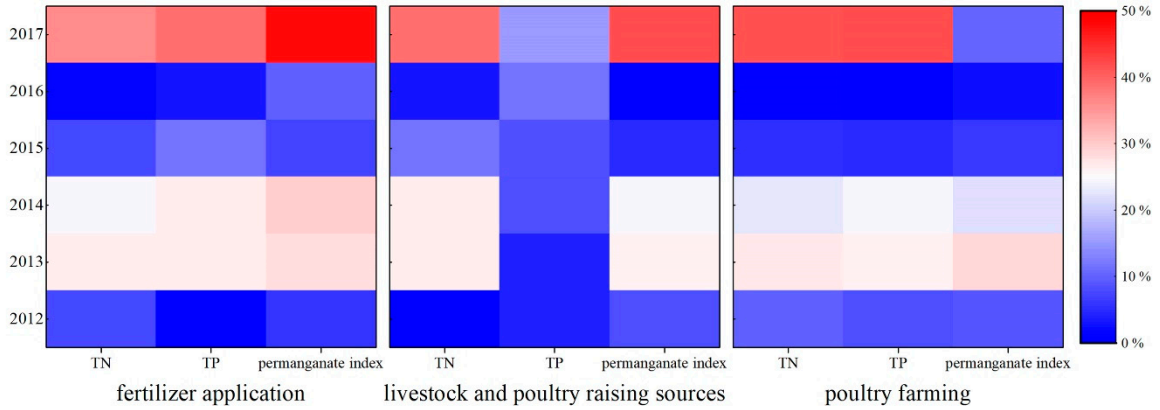


Figure 3. Each sources' contribution to the percentage decrease of export coefficients based on the counterfactual scenarios.

3.3. Environmental Performance Accounting

Environmental performance was calculated in two perspectives: the local performance and delivered performance. Local performance was based on the change of TN, TP, and COD_{Mn} loads generated in local between non-point sources in counterfactual scenarios and realistic situations, while the delivered performance was based on the loads delivered to the XRB's export (Jiekou Section). Delivered yield refers to the net amount of TN, TP, and COD_{Mn} exported per area from the basin after all riverine losses were taken into account [39].

Additionally, environmental performance in XAJ1 was based on the change between XAJ1 and the period of 2007–2011 (before ecological compensation); the environmental performance in XAJ2 should be reflected by the performance strictly in XAJ2, thus it is the result of the changes between XAJ2 and the period of 2007–2011 minus the changes between XAJ1 and the period of 2007–2011.

In Figures 4–6, we found that the local and delivered performance in XAJ1 was better than that in XAJ2; it was more difficult to make much improvement in the areas which had already made improvements. From 2012 to 2017, in the perspective of the net amount, the environmental performance of COD_{Mn} was the best, with the average amount of 7283.32 t and 346.95 t of local performance and delivered performance, respectively. The environmental performance of TN was the second, with the average amount of 73.40 t and 1659.66 t of local performance and delivered performance, respectively. The environmental performance of COD_{Mn} was the best, with the average amount of 7.41 t and 167.53 t of local performance and delivered performance, respectively. The local performance was focused on the main pollution area (She Xian and Tunxi Qu), while the delivered performance shows more spatial distribution.

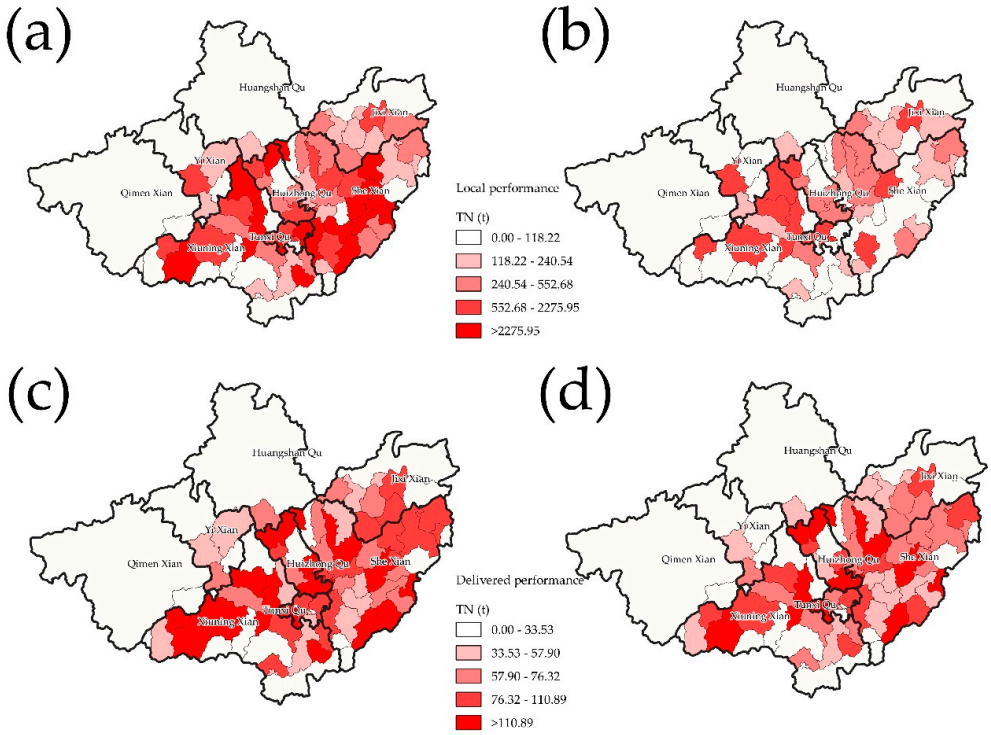


Figure 4. TN's environmental performance: (**a**) local performance in XAJ1; (**b**) local performance in XAJ2; (**c**) delivered performance in XAJ1; (**d**) delivered performance in XAJ2.

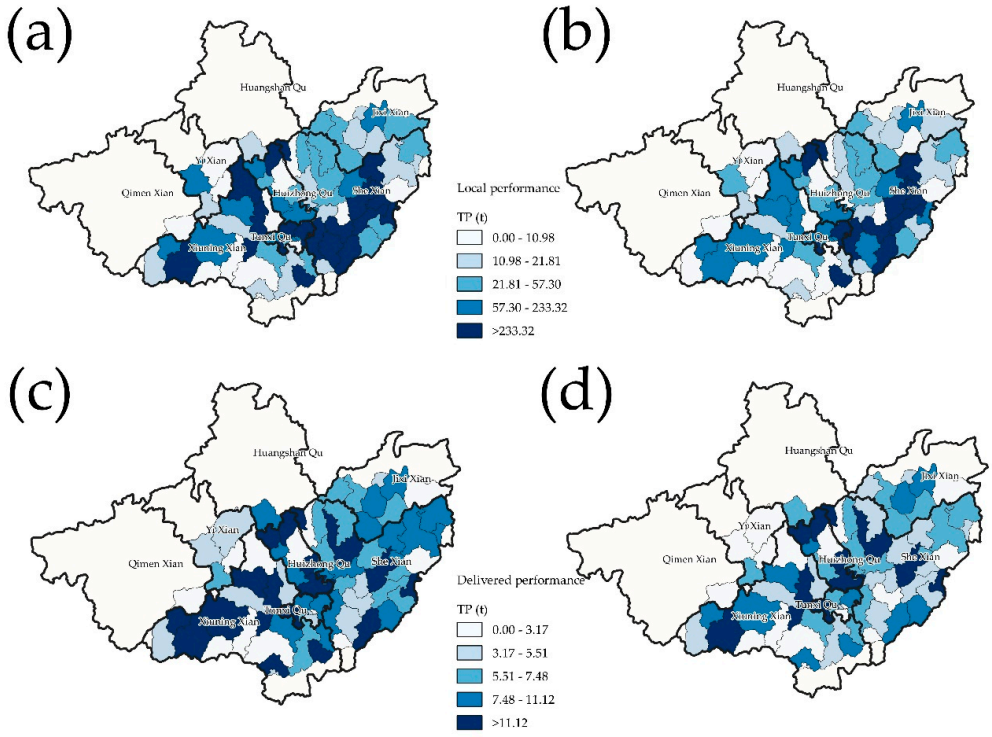


Figure 5. TP's environmental performance: (**a**) local performance in XAJ1; (**b**) local performance in XAJ2; (**c**) delivered performance in XAJ1; (**d**) delivered performance in XAJ2.

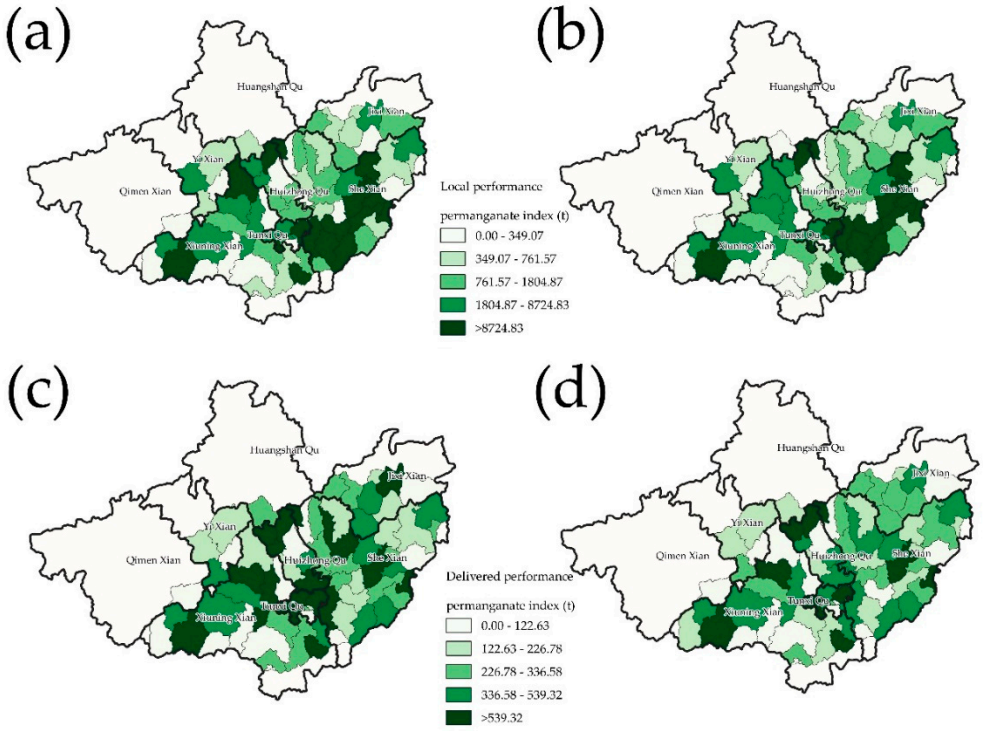


Figure 6. COD_{Mn}'s environmental performance: (**a**) the local performance in XAJ1; (**b**) the local performance in XAJ2; (**c**) the delivered performance in XAJ1; (**d**) the delivered performance in XAJ2.

3.4. Environmental Investment Efficiency Accounting

Table 8 shows the average efficiency of environmental investment, the efficiencies in XAJ1 were much better than that in XAJ2; the average efficiencies based on local performance were 0.270 and 0.156 in XAJ1 and XAJ2, respectively; the average efficiencies based on delivered performance were 0.547 and 0.184 in XAJ1 and XAJ2, respectively. The efficiencies based on delivered performance were much better than that in local performance.

Table 8. The average efficiency of environmental investment in XRB.

	Efficiency Based on Local Performance in XAJ1	Efficiency Based on Local Performance in XAJ2	Efficiency Based on Delivered Performance in XAJ1	Efficiency Based on Delivered Performance in XAJ2
Tunxi Qu	0.370	0.578	0.614	0.616
Huangshan Qu	0.002	0.001	0.145	0.052
Huizhou Qu	0.053	0.023	0.543	0.290
She Xian	0.262	0.054	0.634	0.131
Xiuning Xian	0.087	0.010	0.598	0.103
Yi Xian	0.020	0.005	0.225	0.087
Qimen Xian	1.000	0.002	1.000	0.077
Jixi Xian	0.370	0.578	0.614	0.116
Average	0.270	0.156	0.547	0.184

Table 9 shows the average scale efficiency of environmental investment. The scale efficiencies in XAJ1 were better than that in XAJ2; the average scale efficiencies based on local performance were 0.926 and 0.513 in XAJ1 and XAJ2, respectively. The average scale efficiencies based on delivered performance were 0.841 and 0.544 in XAJ1 and XAJ2, respectively. The scale efficiencies based on

local performance were better than that in local performance in XAJ1, while they were on the contrast in XAJ2.

Table 9. The average scale efficiency of environmental investment in XRB.

	Scale Efficiency Based on Local Performance in XAJ1	Scale Efficiency Based on Local Performance in XAJ2	Scale Efficiency Based on Delivered Performance in XAJ1	Scale Efficiency Based on Delivered Performance in XAJ2
Tunxi Qu	0.878	0.815	0.663	0.648
Huangshan Qu	0.922	0.204	0.820	0.531
Huizhou Qu	0.989	0.687	0.763	0.435
She Xian	0.920	0.464	0.967	0.434
Xiuning Xian	0.818	0.461	0.892	0.459
Yi Xian	1.000	0.599	0.963	0.518
Qimen Xian	1.000	0.058	1.000	0.898
Jixi Xian	0.878	0.815	0.663	0.433
Average	0.926	0.513	0.841	0.544

Table 10 shows the average pure efficiency of environmental investment. The pure technique efficiencies in XAJ1 were better than that in XAJ2; the average pure technique efficiencies based on local performance were 0.285 and 0.244 in XAJ1 and XAJ2, respectively. The average pure technique efficiencies based on delivered performance were 0.658 and 0.362 in XAJ1 and XAJ2, respectively. The pure technique efficiencies based on delivered performance were much better than that in local performance.

Table 10. The average pure technical efficiency of environmental investment in XRB.

	Pure Technical Efficiency Based on Local Performance in XAJ1	Pure Technical Efficiency Based on Local Performance in XAJ2	Pure Technical Efficiency Based on Delivered Performance in XAJ1	Pure Technical Efficiency Based on Delivered Performance in XAJ2
Tunxi Qu	0.390	0.761	0.900	0.928
Huangshan Qu	0.002	0.003	0.177	0.098
Huizhou Qu	0.055	0.057	0.694	0.678
She Xian	0.276	0.251	0.666	0.320
Xiuning Xian	0.148	0.084	0.696	0.280
Yi Xian	0.020	0.007	0.231	0.171
Qimen Xian	1.000	0.027	1.000	0.086
Jixi Xian	0.390	0.761	0.900	0.335
Average	0.285	0.244	0.658	0.362

3.5. Global Sensitivity and Uncertainty Analysis

The uncertainties associated with the results mainly derived from the data regarding the pollutants and the joint models' results. As the first ecological compensation demonstration for crossing provinces of downstream and upstream in China, the data collection was supported and guaranteed by the local government. There is nonetheless some uncertainty that errors in data may affect the results.

In total, 100,000 samples were drawn, and 163,191 parameter sets with ME bigger than 0.8 were retained as behavioral sets accounting for about 16% of the total samples. By assessing parameters and modeling uncertainties of the SPARROW models with the use of the GLUE method, the paper evaluates the results of the environmental investment efficiencies. From the unimodal posterior distributions, parameter estimates can be unambiguously inferred as modal values, while the shape of the distributions indicates the degree of uncertainty of the estimates [33]. By running the model with the behavioral parameter sets, the percentage of the observation coverage of the GLUE method is 88%.

Tables S4–S6 show the sensitivity of individual parameters expressed as the deviation between the cumulative likelihood distribution curves of the posterior and prior parameters. Tables 11–13 show the summary of posterior distribution for each parameter in SPARROW models. Not all the parameters displayed significant sensitivity. SPARROW TN models are highly sensitive to the coefficient of domestic pollution sources, fertilizer application, slope, temperature and k_1; SPARROW TP models are highly sensitive to the coefficient of fertilizer application, drainage density, and k_1; SPARROW COD_{Mn} models are highly sensitive to the coefficient of fertilizer application, slope, and precipitation.

Table 11. Summary of posterior distribution for each parameter in SPARROW TN model coefficients.

		2007–2012						2012–2017					
		Min.	**Max.**	**Mean**	**Median**	**Variance**	**Skewness**	**Min.**	**Max.**	**Mean**	**Median**	**Variance**	**Skewness**
Pollution sources	Point sources	0.161	2.031	0.967	0.919	0.019	0.298	0.179	1.883	0.9322	0.895	0.037	0.216
	Fertilizer application	0.041	0.478	0.227	0.218	0.005	0.200	0.037	0.445	0.2192	0.208	0.004	0.227
	Livestock and poultry raising sources	0.596	10.338	4.764	4.669	0.143	0.160	0.887	8.246	4.4572	4.457	0.089	0.258
	Domestic pollution sources	0.296	4.086	2.128	2.086	0.085	0.200	0.305	4.066	1.9454	1.926	0.058	0.119
Land delivery factor	Slope	−0.0023	−0.0260	−0.0144	−0.0139	−0.0003	0.225	−0.0017	−0.0284	−0.0138	−0.0137	−0.0003	0.255
	Precipitation	0.0006	0.0074	0.0040	0.0039	0.0001	0.219	0.0007	0.0113	0.0052	0.0052	0.0001	0.132
	Temperature	0.0004	0.0040	0.0019	0.0019	0.0001	0.258	0.0004	0.0046	0.0022	0.0021	0.0001	0.108
Water delivery factor	k_1	0.024	0.315	0.152	0.160	0.003	0.181	0.020	0.280	0.1522	0.151	0.005	0.269
	k_2	0.006	0.060	0.032	0.033	0.001	0.173	0.006	0.053	0.0286	0.028	0.001	0.216

Table 12. Summary of posterior distribution for each parameter in SPARROW TP model coefficients.

		2007–2012						2012–2017					
		Min.	**Max.**	**Mean**	**Median**	**Variance**	**Skewness**	**Min.**	**Max.**	**Mean**	**Median**	**Variance**	**Skewness**
Pollution sources	Point sources	0.160	1.862	0.960	0.950	0.038	0.204	0.144	2.120	0.9724	0.963	0.019	0.119
	Fertilizer application	0.002	0.020	0.011	0.011	0.000	0.231	0.002	0.024	0.0126	0.013	0.001	0.312
	Livestock and poultry raising sources	0.084	1.233	0.590	0.578	0.024	0.223	0.100	1.257	0.6906	0.677	0.021	0.203
	Domestic pollution sources	0.002	0.033	0.016	0.016	0.001	0.210	0.003	0.037	0.0184	0.018	0.001	0.244
Land delivery factor	Precipitation	0.0005	0.0071	0.0037	0.0037	0.0001	0.1830	0.0005	0.0063	0.0034	0.0036	0.0001	0.1400
	Slope	−0.0037	−0.0536	−0.0264	−0.0267	−0.0011	0.2390	−0.0044	−0.0620	−0.0330	−0.0327	−0.0010	0.1570
	Drainage density	0.0000	0.0004	0.0002	0.0002	0.0000	0.1530	0.0017	0.0185	0.0090	0.0086	0.0003	0.1650
Water delivery factor	k_1	0.046	0.589	0.305	0.302	0.012	0.201	0.042	0.537	0.2934	0.302	0.012	0.214
	k_2	0.007	0.101	0.049	0.048	0.002	0.210	0.009	0.087	0.0458	0.046	0.001	0.100

Table 13. Summary of posterior distribution for each parameter in SPARROW COD_{Mn} model coefficients.

		2007–2012						2012–2017					
		Min.	**Max.**	**Mean**	**Median**	**Variance**	**Skewness**	**Min.**	**Max.**	**Mean**	**Median**	**Variance**	**Skewness**
Pollution sources	Point sources	0.084	0.930	0.500	0.490	0.015	0.146	0.068	1.046	0.5176	0.507	0.021	0.248
	Fertilizer application	0.407	5.108	2.541	2.490	0.102	0.189	0.334	5.291	2.4048	2.477	0.072	0.186
	Livestock and poultry raising sources	1.603	19.965	10.345	10.552	0.414	0.156	2.019	21.886	10.573	10.996	0.423	0.214
	Domestic pollution sources	1.325	15.502	7.046	7.046	0.211	0.253	0.995	13.320	7.1612	6.803	0.286	0.170
Land delivery factor	Precipitation	0.001	0.009	0.005	0.005	0.000	0.240	0.001	0.008	0.0038	0.004	0.000	0.190
	Slope	−0.010	−0.116	−0.062	−0.063	−0.002	0.210	−0.010	−0.123	−0.0642	−0.063	−0.001	0.323
	Temperature	0.001	0.010	0.005	0.005	0.000	0.141	0.001	0.009	0.0044	0.004	0.000	0.327
Water delivery factor	k_1	0.124	1.916	0.913	0.903	0.037	0.256	0.120	1.473	0.8092	0.809	0.016	0.151
	k_2	0.022	0.261	0.123	0.123	0.005	0.163	0.017	0.223	0.1238	0.130	0.002	0.138

4. Discussion and Conclusions

Given its previous successes in XRB with the junction of Anhui province and Zhejiang province, the experience was used for reference in Jiuzhoujiang River with the junction of Guangxi autonomous region and Guangdong province basin and Hanjiang-Tingjiang River Basin with the junction of Fujian province and Guangdong province as the next two ecological compensation pilots in China. Not surprisingly, similar measures will be used in more and more river basins. The specific influences of ecological compensation demonstration in basin-scale have not been effectively quantified in China, mainly due to the lack of methods to get rid of the influence of natural factors.

This paper makes a substantial exploration of the first ecological compensation, striving to more accurately measure the impact of environmental performance. The results show that the approach of the first ecological compensation demonstration for crossing provinces of downstream and upstream in China is a successful one. The programs have produced many positive ecological outcomes. At the XAJ1, the environmental performances and efficiencies were higher than those in XAJ2. The decrease of non-point source in XAJ2 was better than that in XAJ1, due to the accumulation of the environmental effects. The environmental investments achieved the goals, and both local performance and delivered performance of different sources were great.

With systematic planning and diversified funding, the approach of the compensation was effective. This study deepens our understanding of how to accurately measure the impact of environmental performance, which will provide future researchers with references to establish models to get rid of the natural factors' influences, providing policy makers with a new perspective in the next step of environmental investment optimization.

Supplementary Materials: The following are available online at http://www.mdpi.com/2071-1050/12/15/6021/s1, Figure S1: Composition of compensation funds in XRB in 2012–2017, Table S1: p-Values of SPARROW TN model coefficients calibrated on 60 stations in XRB models, Table S2: p-Values of SPARROW TP model coefficients calibrated on 60 stations in XRB models, Table S3: p-Values of SPARROW CODMn model coefficients calibrated on 60 stations in XRB models, Table S4: Sensitivity of individual parameter of SPARROW TN models, Table S5: Sensitivity of individual parameter of SPARROW TP models, Table S6: Sensitivity of individual parameter of SPARROW CODMn models.

Author Contributions: Conceptualization, G.L. (Guoguang Li); data curation, Q.W. and G.L. (Guihuan Liu); methodology, G.L. (Guoguang Li); software, S.P.; supervision, Y.Z. and Y.W. (Yanjie Wei); writing—original draft, G.L. (Guoguang Li); writing—review and editing, Y.W. (Yuqiu Wang) and J.W. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the Major Science and Technology Program for Water Pollution Control and Treatment (2017ZX07301-001) and the Fundamental Research Funds for the Central Public Welfare Research Institutes (Grant No. TKS170219, TKS170218, TKS190202, TKS190106).

Acknowledgments: We are grateful to the editor and the reviewers for their valuable comments and suggestions.

Conflicts of Interest: The authors declare no conflicts of interest.

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