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Evaluating Effects of Nitrogen and Phosphorus Discharges under Different Reduction Scenarios: A Case of Chaohu Lake Basin, China

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Abstract: Determining the amount of nitrogen (N) and phosphorus (P) discharged into lakes and assessing the effectiveness of reduction measures in a basin that involve the interaction of multiple factors are still daunting challenges. In this study, the random forest (RF) model was employed to simulate the impact of controlling measures on the amount of N and P discharged in 2025 under seven specific reduction scenarios. Discharged N and P decreased in the basin by 23.38% and 31.69% from 2011 to 2020, respectively. The N and P nutrient discharge intensities were significantly higher in the western part of the basin (13.31 $kg \cdot ha^{-1} \cdot a^{-1}$ and 1.34 $kg \cdot ha^{-1} \cdot a^{-1}$) than those in the eastern region (10.24 $kg \cdot ha^{-1} \cdot a^{-1}$ and 0.74 $kg \cdot ha^{-1} \cdot a^{-1}$). Fertilizer runoff (N: 34.72%, 5934.49 t; P: 13.60%, 199.76 t), domestic sewage (N: 29.14%, 4009.27 t; P: 34.84%, 496.59 t), and livestock farming (N: 15.11%, 2657.50 t; P: 40.05%, 616.05 t) were the key sources of N and P. The RF model shows that ($R^2 > 0.994$, $p < 0.01$) the multi-factor reduction effect is the best, and under this discharge reduction effect, the amount of N and P discharged in 2025 are expected to decrease by 13.79% and 19.42%, respectively, compared with those in 2020. In addition, different key sources in sub-basins might lead to regional differences in the discharge reduction effects of various measures. Ultimately, we recommend that the synergistic treatment of point and non-point sources, using treatments with multiple measures, should be implemented in different regions to reduce the amount of N and P discharged in the Chaohu Lake Basin.

Keywords: Chaohu Lake Basin; nutrient discharge; source identification; discharge reduction effects; scenario simulation

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1. Introduction

In the past two decades, many lakes in China have experienced lake eutrophication due to excessive total nitrogen (TN) and total phosphorous (TP) discharge from human activities [1,2]. This phenomenon has caused an array of environmental problems, such as cyanobacterial blooms, a decline in biodiversity, and degradation of the ecosystem balance [3]. Although point source pollution has been controlled effectively in China, non-point source pollution has become the primary source of water eutrophication [4,5]. Point- and non-point pollution from human activities such as domestic sewage, industrial sewage, agricultural runoff, and atmospheric deposition substantially affects the TN and TP loads of lakes [6,7]. Hence, effectively controlling the amount of N and P discharged plays a key role in managing water eutrophication in the basin.

The amount of N and P discharged can be quantified using non-point source models, such as the Storm Water Management Model (SWMM), Areal Nonpoint Source Watershed Environmental Response Simulation model (ANSWERS), Agricultural Non-Point Source Pollution model (AGNPS), Integrated Valuation of Ecosystem Services and Tradeoffs model (InVEST), Soil and Water Assessment Tool (SWAT), and modified export coefficient model [8–13]. The SWMM can simulate a fully dynamic hydraulic route, but it is applied to urban areas [14]. The ANSWERS model has high requirements for the hydro-geological conditions of the basin [15,16]. The AGNPS model is used to simulate several variables from a single rainfall event, such as runoff, N, and P, in small- and medium-sized agricultural basins [17]. The InVEST and SWAT models have been widely used to model material circulation and quantify results in basins, mainly by calculating the runoff path using the Digital Elevation Model (DEM) slope. Both InVEST and SWAT can yield accurate results for some basins with a large topographic relief [18]. However, there is uncertainty around the outcomes of these models for low-lying and flat basins [19]. Of these models, the modified export coefficient method has exhibited a promising performance since it relies on readily obtained, relevant, and reliable datasets. Over several decades, the model has been continuously improved, covering a wider range of nitrogen and phosphorus accounting methods [20], and it has achieved significant results in previous studies [21,22].

In addition to modeling workflows, machine learning techniques such as support vector machines (SVMs), the K-nearest neighbor (KNN), and random forest (RF) were used to predict the amount of N and P discharged in a basin [23–25]. SVMs have unique advantages in solving recognition problems, such as small samples and nonlinearity, but they still need other algorithms to solve multi-class classification problems [26]. The KNN algorithm is theoretically simple and easy to implement, but the prediction bias is large when the training samples are not balanced [27]. In contrast, RF models can still maintain a high prediction accuracy under multiple complex factors. Moreover, the advantages of RF models include high precision, high efficiency, and strong interpretability, which enable these models to be widely used in logic judgment and regression simulation studies [28].

In recent decades, Chaohu Lake, one of China's three eutrophic lakes alongside Tai Lake and Dian Lake, has attracted worldwide attention [29]. In the Chaohu Lake Basin, large amounts of nitrogen, phosphorus, and other nutrients generated by high-intensity human activities are discharged into the lake through surface runoff, causing serious non-point source pollution and leading to severe eutrophication of Chaohu Lake [30]. Current studies have focused on the water quality, source identification, and interface exchanges of N and P in Chaohu Lake [31]. However, there is little information on the discharge reduction effects of N and P. Determining how to quantitatively evaluate the effectiveness of treatment measures will become the key to managing the future water quality in the Chaohu Lake Basin. Thus, it is necessary to quantify the spatio-temporal dynamics of N and P discharge in this basin and link the obtained information to water protection policies.

Therefore, the main objects of this research were to identify the source of N and P discharge in the Chaohu Lake Basin, and evaluate the potential reduction effects under different scenarios. Specifically, the contributions of this paper are divided into three parts: (1) a modified export coefficient method was used to quantify the amount of N and P discharge and analyze their spatial–temporal distributions; (2) the key sources of N and P discharge were identified by combining RDA models; and (3) the RF model was used to evaluate the reduction effects of N and P discharges under different scenarios.

2. Materials and Methods

2.1. Study Area

The Chaohu Lake Basin (30°58′ N~32°06′ N, 116°24′ E~118°00′ E), located in central Anhui Province, China, consists of 12 counties within Hefei, Liuan, Wuhu, and Maanshan (Figure 1) [31]. The western part of the basin has high elevation, while the eastern part has low elevation with low-lying and flat terrain [19]. Chaohu Lake is the fifth largest freshwater lake in China, with an average depth of 2.69 m and an area of about 780 km^2 [32,33].

Consequently, the river system of Chaohu Lake flows into the lake radially, and mainly includes eight rivers (the Nanfei, Shiwuli, Pai, Hangbu, Zhegao, Shuangqiao, Zhao, and Baitianshi Rivers) that flow into the lake, and one river (the Yuxi River) that flows out of the lake [34]. With the rapid population growth and rapid economic development within the basin, a large amount of industrial sewage, domestic sewage, and agricultural runoff are being discharged into the lake, resulting in the excessive enrichment of N and P elements, and the frequent occurrence of cyanobacteria [30]. Although many water environment management measures are continuously applied for the management of water quality in Chaohu Lake, the water quality in the western half of Chaohu Lake is still poor (belongs to class V (TN = 2 mg·L^{-1}, TP = 0.2 mg·L^{-1}) in accordance with GB 3838-2002) [35] according to the "2021 Anhui Province Ecological and Environmental State of the Communique" (https://sthjt.ah.gov.cn/, accessed on 2 October 2023).

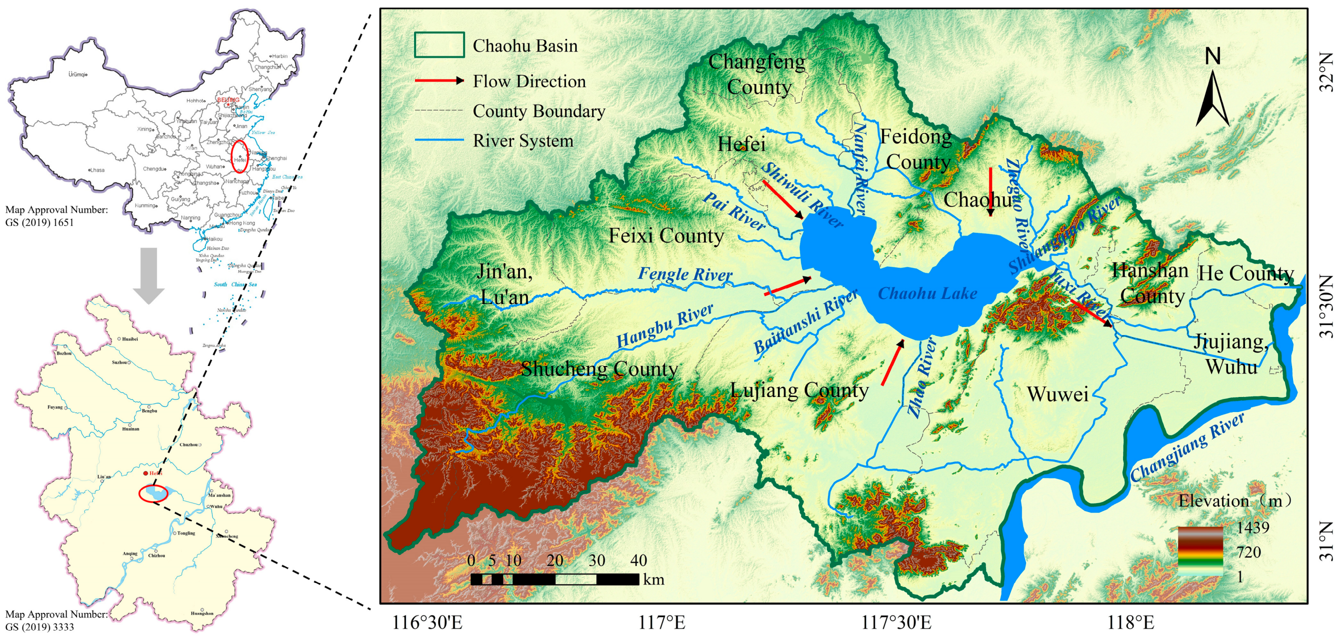

Figure 1. Location of Chaohu Lake Basin.

2.2. Methods

2.2.1. Accounting for Point and Non-Point Source Pollution

The modified export coefficient method has been used widely to estimate the non-point source pollution generated by various sources [21]. Considering its promising performance, this research used the modified export coefficient method to quantify N and P discharge in the Chaohu Lake Basin from four major sources: fertilizer runoff, livestock breeding, aquaculture, and atmospheric N deposition. In addition, point source pollution, such as from domestic sewage and industrial sewage, was calculated using the Pollutant Production and Blowdown Coefficient [36]. All the socio-economic data used were obtained from the 2011–2020 statistical yearbooks of each county in Anhui Province. Additionally, the pollution sources and equations were cited from the National Second Pollution Source Census Manual of Production and Discharge Coefficients (http://www.mee.gov.cn, accessed on 2 October 2023).

(1) Domestic sewage

$$W_j = \sum_i S_i \cdot \left(WU_{ij} + WV_{ij}\right) \tag{1a}$$

$$WU_{ij} = WUp_{ij} - WUd_{ij} \tag{1b}$$

$$WUp_{ij} = SUp_i \cdot (1 - Rw) \cdot Pc_{ij}/100 \tag{1c}$$

$$SUp_i = Rp_i \cdot Pw_i \cdot Rf_i \cdot 365/1000 \tag{1d}$$

$$WUd_{ij} = SUp_i \cdot Sd_i \cdot (1 - Rw) \cdot (Ic_i - Oc_i)/100 + SUp_i \cdot Rw \cdot Ic_i/100 \tag{1e}$$

$$WV_{ij} = Vp_i \cdot Pi_i \cdot 365/100 \cdot (1 - Vs_i \cdot Cr_i) \tag{1f}$$

where W_j is the discharge of pollutant j in domestic sewage in the basin (t·a^{-1}). S_i is the ratio of the area i in the basin to the administrative area. WU_{ij} and WV_{ij} represent the discharge of pollutant j in urban and rural domestic sewage in area i (t·a^{-1}). WUp_{ij} (WUd_{ij}) refers to the amount of pollutant j produced (removed) in urban domestic sewage in area i (t·a^{-1}). SUp_i is the amount of urban domestic sewage generated in area i (t·a^{-1}). Rw is the renewable water utilization rate in urban region i [37]. Pc_{ij} represents the pollution concentration coefficient of pollutant j in urban domestic sewage in area i (mg·L^{-1}). Rp_i and Vp_i are the urban and rural resident population in area i. Pw_i refers to the coefficient of comprehensive water consumption per capita in urban area i (L·person^{-1}·d^{-1}). Rf_i is the discount factor in urban area i. Sd_i represents the urban domestic sewage treatment rate in area i. Ic_i and Oc_i refer to the weighted average inlet and outlet concentrations of domestic sewage treatment plants in area i (mg·L^{-1}). Pi_i is the pollution production intensity of rural domestic sewage in area i (g·person^{-1}·d^{-1}). Vs_i is the proportion of administrative villages in area i that treat domestic sewage. Cr_i represents the combined removal rate of rural domestic sewage in area i.

(2) Industrial sewage

$$E_j = \sum\nolimits_{il} S_i \cdot Uw_i \cdot \left[P_{lj} \cdot Mt_l \cdot \left(1 - N_{lj} \cdot K_l\right)\right] \tag{2}$$

where E_j represents the discharge of pollutant j caused by industry in the basin (t·a^{-1}). Uw_i is the ratio of urban water withdrawal in area i to the total water withdrawal in the prefecture-level city. P_{lj} refers to the pollution production coefficient of pollutant j from industry l. Mt_l is the amount of raw materials used by industry l (t·a^{-1}). N_{lj} is the l industrial end-of-pipe treatment average removal rate. K_l represents the actual operating rate of l industrial governance facilities.

(3) Fertilizer runoff

$$Cf_{N/P} = \sum\nolimits_i S_i \cdot P_{iN/P} \cdot Fr_{N/P} \tag{3}$$

where $Cf_{N/P}$ represents the amount of N/P loss in agricultural land in the basin (t·a^{-1}). $P_{iN/P}$ is the discounted N/P fertilizer application in area i (t·a^{-1}). $Fr_{N/P}$ refers to the N/P runoff coefficient of agricultural land in the basin [38–40].

(4) Livestock breeding

$$I_j = \sum\nolimits_{iv} S_i \cdot (Lse_{ivj} + Nse_{ivj}) \times 0.001 \tag{4a}$$

$$Lse_{ivj} = Lst_{iv} \cdot Lsc_{ivj} \tag{4b}$$

$$Nse_{ivj} = Nst_{iv} \cdot Nsc_{ivj} \tag{4c}$$

where I_j refers to the discharge of pollutant j due to livestock breeding in the basin (t·a^{-1}). Lse_{ivj} and Nse_{ivj} represent the pollutant discharge caused by livestock and farmers j in area i (t·a^{-1}). Lst_{iv} and Nst_{iv} are the number of livestock being bred and farmers in area i [41]. Lsc_{ivj} and Nsc_{ivj} represent the pollutant discharge coefficients of livestock and farmers j in area i (kg·head^{-1}·a^{-1}).

(5) Aquaculture

$$Q_j = \sum\nolimits_i S_i \cdot Ay_i \cdot Ad_{ij} \times 0.001 \tag{5}$$

where Q_j is the discharge of j pollutants in aquaculture in the basin ($t \cdot a^{-1}$). Ay_i refers to the aquaculture production in area i ($t \cdot a^{-1}$). Ad_{ij} represents the pollutant discharge coefficient of aquaculture j in area i.

(6) Atmospheric N deposition

$$N_d = \sum_i Wa_i \cdot Nf \tag{6}$$

where N_d refers to the atmospheric N deposition in the basin (t). Wa_i is the area of inland waters in area i (ha). Nf ($kg \cdot ha^{-1} \cdot a^{-1}$) represents the basin N deposition flux [42–44].

2.2.2. Random Forest (RF) Model

A random forest (RF) model is a multi-decision tree-based machine learning approach for the prediction of continuous and categorical variables. RF employs bagging or bootstrapping to generate many decision trees, where each decision tree will respond to each set of predicted values during evaluation [45]. Compared to other decision tree algorithms and machine learning algorithms based on classification systems, the model can produce better effects in practical applications [46]. In this study, the samples (i.e., domestic sewage, industrial sewage, fertilizer runoff, livestock breeding, aquaculture, and atmospheric deposition) were randomly divided, with 80% assigned for training and 20% for testing, and with a constraint for avoiding overlapping between the testing and training samples. The criteria for assessing developed models were $R^2 > 0.994$ and $p < 0.01$.

2.2.3. Developing Scenarios

To better reveal how N and P loads and regional water quality vary in response to different discharge reduction measures, seven simulation scenarios were set up in this study based on local N and P reduction policies (Table 1). The amount of N and P discharge in the Chaohu Lake Basin and in various regions within the basin were predicted for 2025.

Table 1. Scenario setting for simulating N and P discharge reduction effects.

Name	Abbreviation	Management Measures
Single-factor	S1	fertilizer application
	S2	domestic sewage
	S3	livestock breeding
Dual-factor	S1-3	fertilizer application and domestic sewage
	S2-3	domestic sewage and livestock breeding
	S1-2	fertilizer application and domestic sewage
Multi-factor	S1-2-3	fertilizer application, domestic sewage, and livestock breeding

2.2.4. Parameter Uncertainty and Sensitivity Analysis

To gain insight into the influence of parameter input uncertainties on the final results, an analysis was performed for the parameters in the above methods by using Monte Carlo and a sensitivity index, which can reduce the error caused by parameter selection [47,48].

Monte Carlo analysis was used to determine which parameters contributed most to the uncertainty of the output variable. The procedure was divided into three steps: (1) all of the parameters were selected; (2) the selected parameters were subjected to simulations; and (3) the uncertainty in the response to the variables was quantified. This procedure was carried out using 10,000 Monte Carlo simulations and the following equations [49]:

$$R_i = RAND(\ ) \cdot (MAX_i - MIN_i) + MIN_i \tag{7}$$

where $RAND()$ is a function generating random numbers between 0 and 1; i is the parameter type; and MAX and MIN are the maximum and minimum values of the parameter range, respectively.

The sensitivity index was used to assess the sensitive parameters in the model. A step-wise regression model was developed using the total N and P loads as dependent variables and their corresponding influencing parameters as independent variables. The change rate of the parameters was considered to be ±10%. Then, the sensitivity index was calculated using Equation (8) [50].

$$I = \frac{\Delta Y_i / Y_i}{\Delta X_i / X_i} \quad (8)$$

I is the sensitivity index; X_i is a parameter of i; Y_i is the output of the model; and ΔX_i and ΔY_i represent the variation in the parameters and outputs, respectively. The larger the absolute value of the index, the more flexible the sensitivity of the parameter to the model, and the more prominent its role in the model [50]. The analysis results show that the N and P runoff coefficient for agricultural land, the production coefficient of N and P for urban domestic sewage, and the coefficient of comprehensive water consumption per capita in urban areas had the most significant effect on the model performance.

2.3. Statistical Analysis

All parameters and statistical data were statistically analyzed using SPSS, Excel, and Origin 2022 software. Pearson's correlation analysis and RDA modeling were used to identify the key sources of N and P discharge. A paired-sample *t*-test was used to validate the significance level between N and P concentrations and influencing factors. With the Anaconda 3 software, the Python language was used to predict N and P discharge through regression analysis and analysis of variance. In addition, temporal and spatial visualization was analyzed using ArcGIS 10.2 software.

3. Results and Discussion

3.1. Spatial–Temporal Distribution of N and P Discharge

The amount of N and P discharge in the Chaohu Lake Basin first increased and then decreased during the 2011–2020 period, with an overall decreasing trend (Figure 2). The total amounts of N and P discharged were 14,500.81 t and 1129.61 t in 2020, respectively, which were 23.38% and 31.69% lower than those in 2011 (18,926.43 t and 1653.67 t). The discharge amounts from non-point sources decreased by 34.9% (N) and 48.9% (P) from 2011 to 2020, respectively. In contrast, the discharge amounts from point sources showed an upward trend, rising by 3.69% (N) and 0.32% (P), respectively. Meanwhile, the amount of N and P discharge from fertilizer runoff, livestock breeding, and domestic sewage accounted for 78.97% and 88.13% of the total discharge recorded in the basin for these two elements. Between 2011 and 2020, the discharge from fertilizer runoff decreased by 30.93% (N) and 16.05% (P), and that from livestock breeding decreased by 63.26% (N) and 62.35% (P). It is noteworthy that the discharge from domestic wastewater increased by 4.76% (N) and 5.59% (P). In the same period, the contribution of fertilizer runoff (from 36.97% to 33.33%) and livestock breeding (from 18.51% to 8.87%) to the discharge of N decreased, whereas that of domestic sewage increased from 25.10% to 34.32%. The contribution of the same sources to P discharge in fertilizer runoff increased from 11.97% to 14.71%, in domestic sewage increased from 29.16% to 45.07%, and in livestock breeding decreased from 48.59% to 26.78%. In addition, the TN and TP concentrations in Chaohu Lake did not show a correlation with the amount of N and P discharge in the Chaohu Lake Basin from 2011 to 2018. A potential explanation is that the TN and TP concentrations are affected by human activities, meteorological conditions, and material transformation [51].

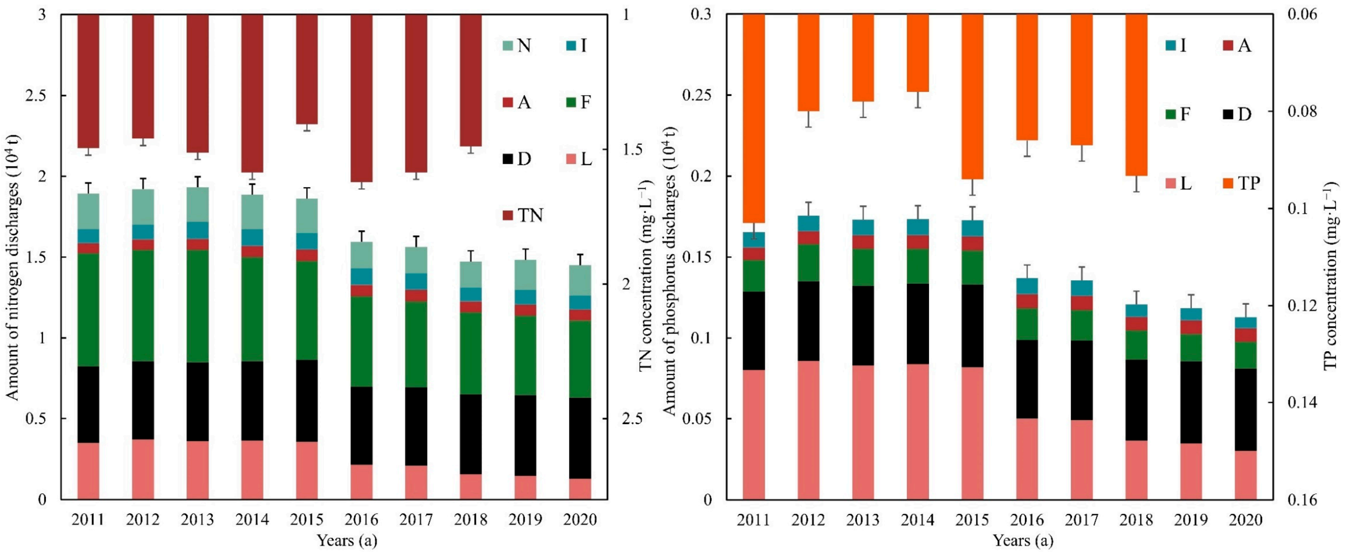

Figure 2. The amounts of nitrogen (N) and phosphorus (P) discharged from various pollution sources in the Chaohu Lake Basin from 2011 to 2020 (Note: N, I, A, F, D, and L represent N deposition, industrial sewage, aquaculture, fertilizer runoff, domestic sewage, and livestock breeding, respectively).

The intensity of the N and P discharge was higher in the western region of the basin than that in the east (Figures 3 and 4). The TN and TP concentrations were higher in the western part of the lake than those in the eastern section, and nutrient concentrations in the estuary near the former were also higher [31]. From 2011 to 2020, the highest N and P discharge intensity was in Hefei (N: 25.11 kg·ha^{-1}, P: 2.37 kg·ha^{-1}), and the lowest was in He County (N: 7.10 kg·ha^{-1}, P: 0.58 kg·ha^{-1}). The intensity of the N and P discharge decreased significantly by 38.79% (N) and 47.14% (P) in Changfeng County, and by 47.82% (N) and 60.81% (P) in Feixi County. However, the discharge intensity in Hefei increased by 13.99% (N) and 19.34% (P) during the 2011–2020 period. The contribution of each pollution source to the N discharge in the Hefei area differed from that in other regions due to high amounts of domestic sewage, atmospheric N deposition, and industrial sewage. All three collectively accounted for 91.63% of the total annual N discharge in Hefei. In particular, the contribution of point sources (i.e., domestic sewage and industrial sewage) was 84.96%. The overall N and P discharge in the Chaohu Lake Basin showed similar spatial–temporal variations.

From 2011 to 2020, the amount of N and P discharge from fertilizer runoff and livestock breeding showed a significant decreasing trend due to the implementation of protection measures such as fertilizer application (e.g., formula fertilization) and livestock breeding (e.g., large-scale breeding). However, the amount of N and P discharge form domestic sewage increased because of the proliferation of the urban population in the basin, as the urban population increased by 66.58% in 2020 compared with that in 2011. Among the major cities in this basin, the urban population of Hefei City (capital of Anhui Province) accounts for 59.15% of the total population in the basin. The population expansion gave rise to an increase in the amount of N and P discharge caused by domestic sewage (i.e., from 1794.22 t in 2011 to 2209.21 t in 2020) [52]. Moreover, this city had the highest contribution amount of N and P from domestic sewage in the basin (N: 41.87%; P: 44.22%) in comparison with other cities. In 2020, the sewage treatment rate in Hefei was 95.39%, reaching saturation. Therefore, more effective measures need to be adopted to reduce the impact of domestic sewage in this area.

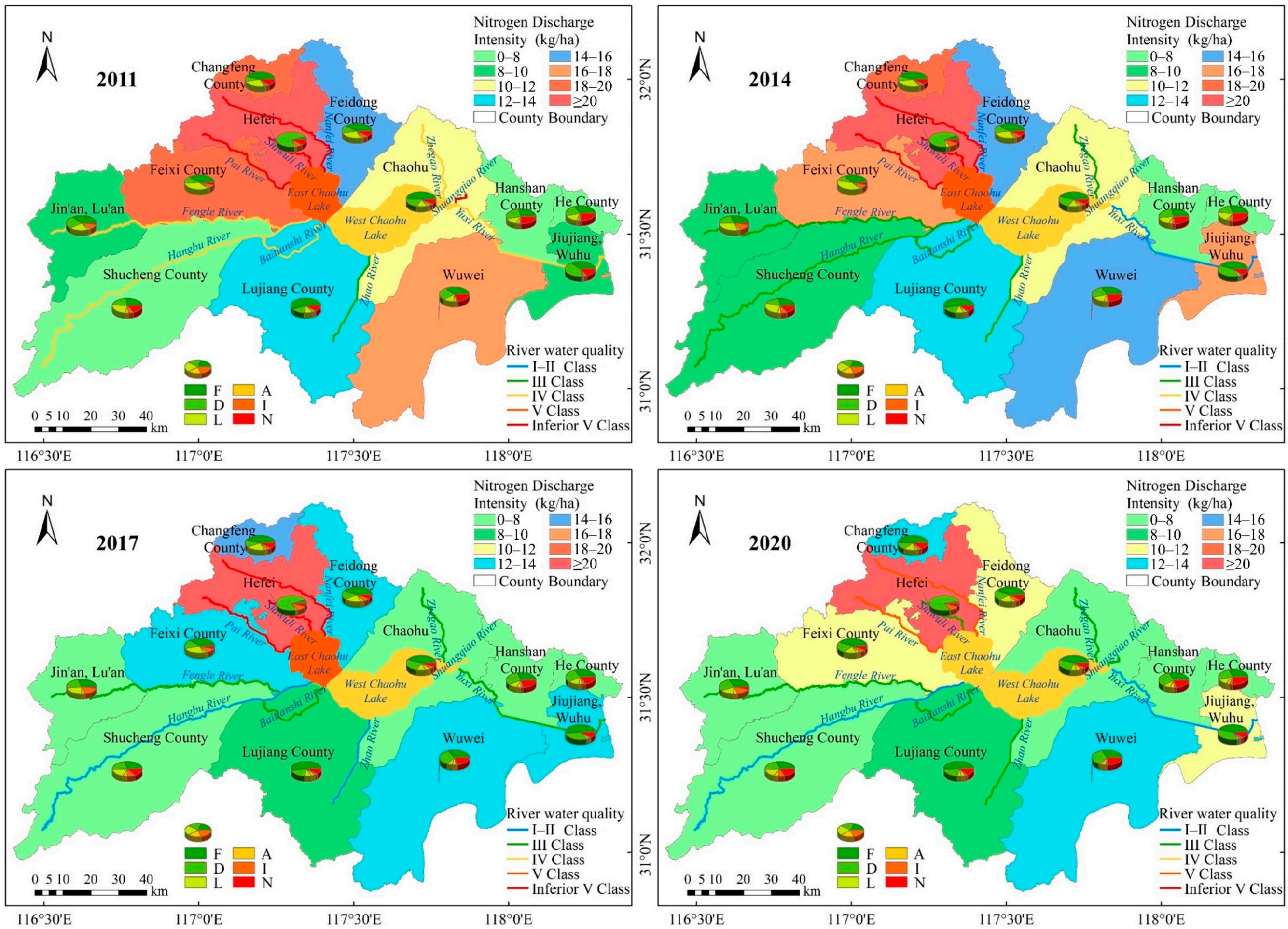

Figure 3. Spatial–temporal distribution of N discharge intensity in Chaohu Lake Basin (Note: F, D, L, A, I, and N represent fertilizer runoff, domestic sewage, livestock breeding, aquaculture, industrial sewage, and N deposition, respectively).

The intensity of the N and P discharge was higher in the western area of this basin than in the east, which primarily explains why the water quality is superior in the eastern part of the lake than in the western region [31]. Therefore, further reduction measures should be applied in the western part of this basin. It is noteworthy that the urbanization rate of the Hefei urban area has increased from 83.26% in 2011 to 96.17% in 2020. The extremely high urbanization rate may suggest that point source pollution (domestic and industrial sewage) intensified the N and P discharge intensity in this area. In contrast, Changfeng and Feixi Counties consist of many farming activities, which are key sources of N and P discharge (the annual contribution of agricultural N and P in Changfeng County is 75.21% and 82.73%, and in Feixi County it is 74.95% and 78.68%). Therefore, the response to agriculture-related N and P discharge reduction measures was positive, and the N and P discharge intensity of the two counties decreased significantly during the 2011–2020 period (Changfeng County: N and P decreased by 7.62 and 1.02 kg·ha^{-1}, respectively; Feixi County: N and P decreased by 9.81 and 1.56 kg·ha^{-1}, respectively). Consequently, the difference in the spatial–temporal change in the N and P discharge reduction effects may be caused by different industrial structures to a certain extent [53].

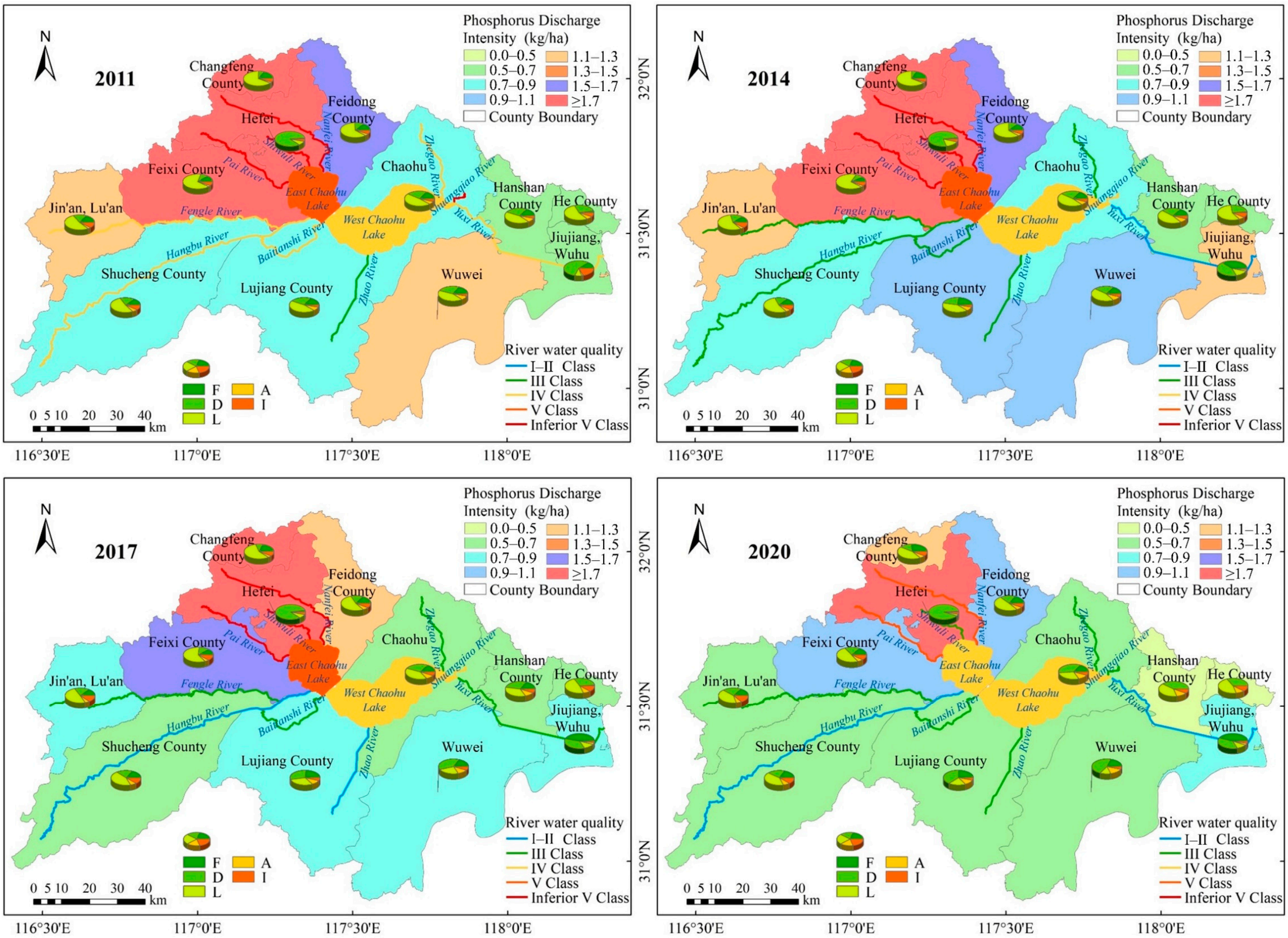

Figure 4. Spatial–temporal distribution of P discharge intensity in Chaohu Lake Basin (Note: F, D, L, A, and I represent fertilizer runoff, domestic sewage, livestock breeding, aquaculture, and industrial sewage, respectively).

3.2. Key Source Identification of N and P Discharge

This study analyzed the effects of social and natural factors on TN and TP concentrations in Chaohu Lake. These factors were N fertilizer application intensity (NFAI), P fertilizer application intensity (PFAI), urban population (UP), rural population (RP), pig feeding (Pig), cattle feeding (Cattle), sheep feeding (Sheep), poultry feeding (Poultry), aquaculture (Aquatic), industrial sewage (IW), and atmospheric N deposition (ND). The correlation analysis did not identify any significant correlations between the TN and TP concentrations and these factors (Figure 5). This is in part due to the TN and TP concentrations in the rivers being affected by multiple factors, such as human activities, meteorological conditions, and material transformation, when these nutrients are transported to the lake [51,54].

The above phenomenon may be caused by multiple factors. For instance, the establishment of bypass multistage artificial wetlands is shown to be effective in reducing N and P, while their removal effects were significantly affected by seasonal changes [55]. Moreover, there are different meteorological conditions in the sub-basins, and rainfall and rainfall intensity will affect the extent to which rainfall runoff flushes nutrients from the surface [56,57]. Moreover, the materials containing N and P undergo structural changes during transport; for example, through denitrification, the NO_{3^-} in the water body is converted into N_2 and N_2O [54]. The construction of gates and dams in rivers to regulate water storage has resulted in a slower water flow and decreased water disturbance in the Chaohu Lake region, which has led to the adsorption of particulate P onto sediments and the interception of N and P nutrients in the water body [58,59]. All of the above-mentioned factors significantly modify N and P contents during the migration process. Therefore, the correlation between the water quality of the three rivers flowing into the Chaohu Lake Basin and the amount of N and P discharged in the corresponding areas was examined. A significant positive correlation was detected, suggesting that the water quality of the rivers in the region is influenced by the N and P discharge (Table S1).

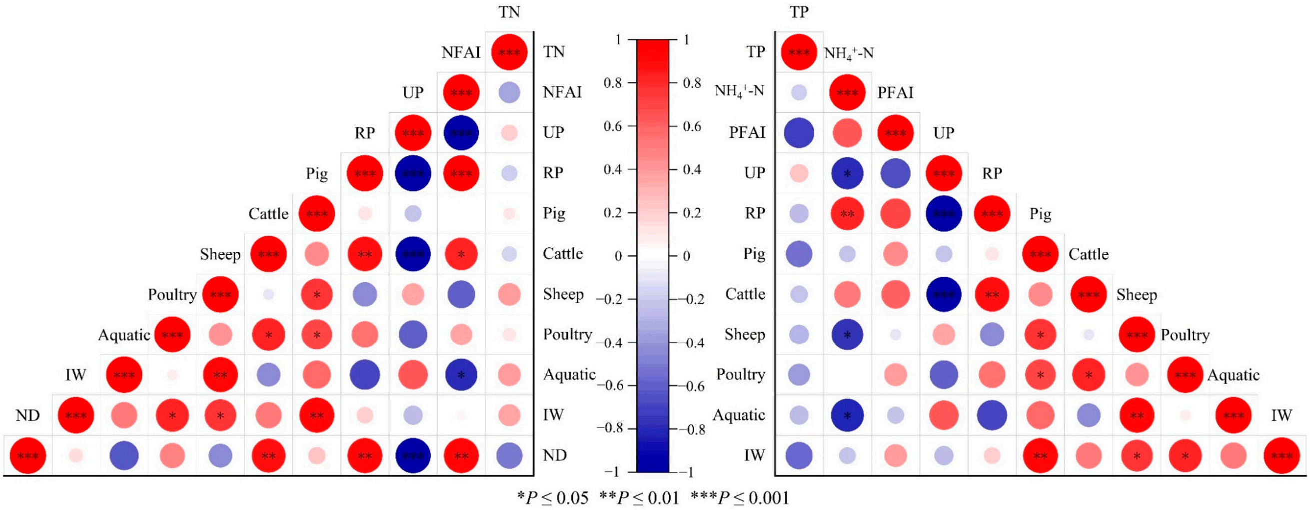

Figure 5. Correlation analysis of TN and TP concentrations with pollution factors.

The accuracy of the correlation analyses conducted in this study was affected by multi-factor conditions. RDA, a qualitative analysis method based on the principle of regression analysis, is used to rank and downscale factors according to their contribution, which can effectively reduce the uncertainty caused by the coupling of multiple factors [60]. In this research, pollution factors were analyzed through RDA, taking into account the TN and TP concentrations and river water quality levels (Figure 6). The results show that the two axes together explained 72.61% of the changes in the TN and TP concentrations in the lake. Specifically, the main influencing factors were fertilizer application, domestic sewage, and livestock farming, contributing 8.7%, 11.1%, and 43.6%, respectively.

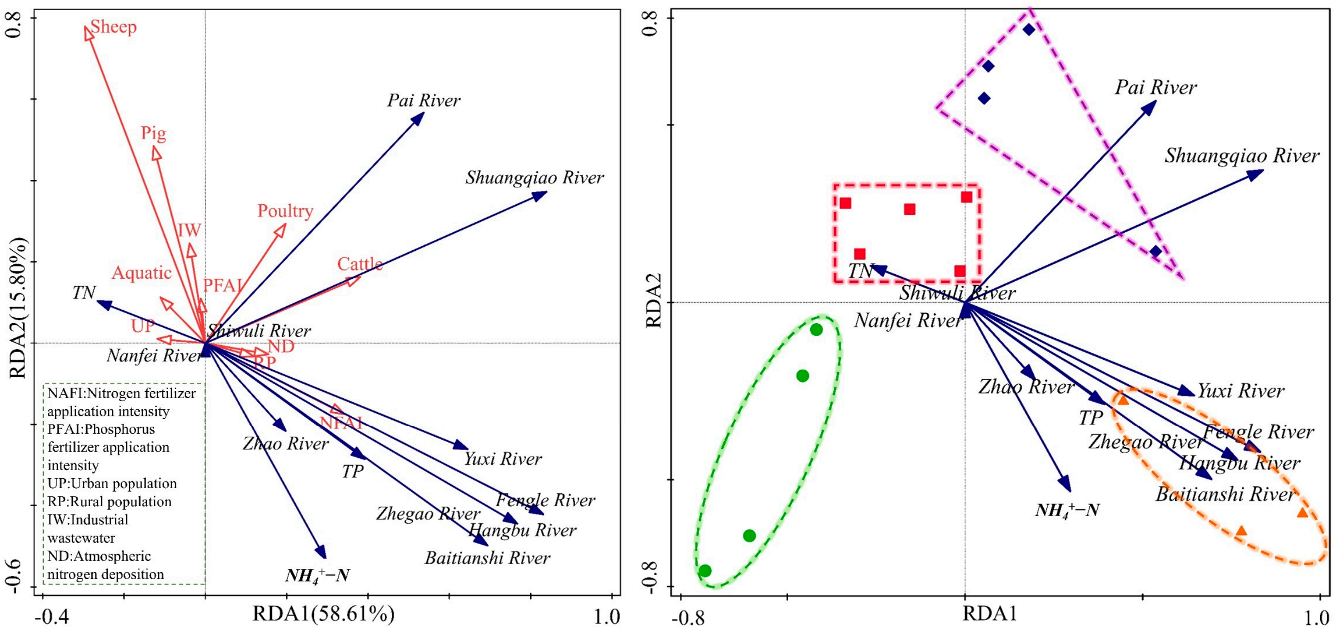

Figure 6. RDA analysis of environmental factors and TN and TP contents in the lake.

Influenced by the coupling of different key sources, river water quality showed significant spatial clustering. Specifically, the water quality of the Zhao, Zhegao, Baitianshi, Hangbu, Fengle, and Yuxi Rivers between 2012 and 2020 was better than the Class III standard and showed spatial clustering. The coupling effect of anthropogenic activities such as fertilizer application, domestic sewage, and livestock breeding played a key role in the variation in the river water quality in the Chaohu Lake Basin. However, in different river systems within this basin, the contribution of each factor is different. A few rivers with poor water quality (i.e., the Nanfei, Shiwuli, and Pai Rivers), which is mainly due to discharges from domestic sewage and livestock breeding, are concentrated in the western part of the basin near Feixi and Feidong Counties and Hefei City [61]. The amount of N and P discharge from livestock breeding in Feixi County was consistent with the water quality variation in the Pai River (t_N = 6.592 and t_P = 6.453, p < 0.01). It was shown that livestock breeding had a significant effect on the water quality (N contribution: 31.12%; P contribution: 63.68%). From 2011 to 2019, the water quality of the Nanfei River was greater than the Class V standard (TN = 2 mg·L^{-1}, TP = 0.2 mg·L^{-1}) of the national standard of surface water quality (GB 3838-2002) [35], mainly due to the high level of the amount of N and P discharge from Hefei all year round.

3.3. Simulation of the N and P Discharge in the Basin

The simulation results from the RF model showed that R-squared of the fitted model was higher than 0.99, which fulfilled the research requirements (Figure 7). However, during the simulation process, when all sub-basins were simulated at the same time, the amount of N and P discharge in some regions was overestimated. For example, in 2020, the discharge amount of P in Chaohu City was overestimated by 8.58%. In addition, in Changfeng County, the discharge amount of N was overestimated by 10.94% in 2018. In addition, the most obvious overestimation phenomenon occurred in the Jiujiang District, where nitrogen was overestimated by 25.54% in 2014 (Figure 7c).

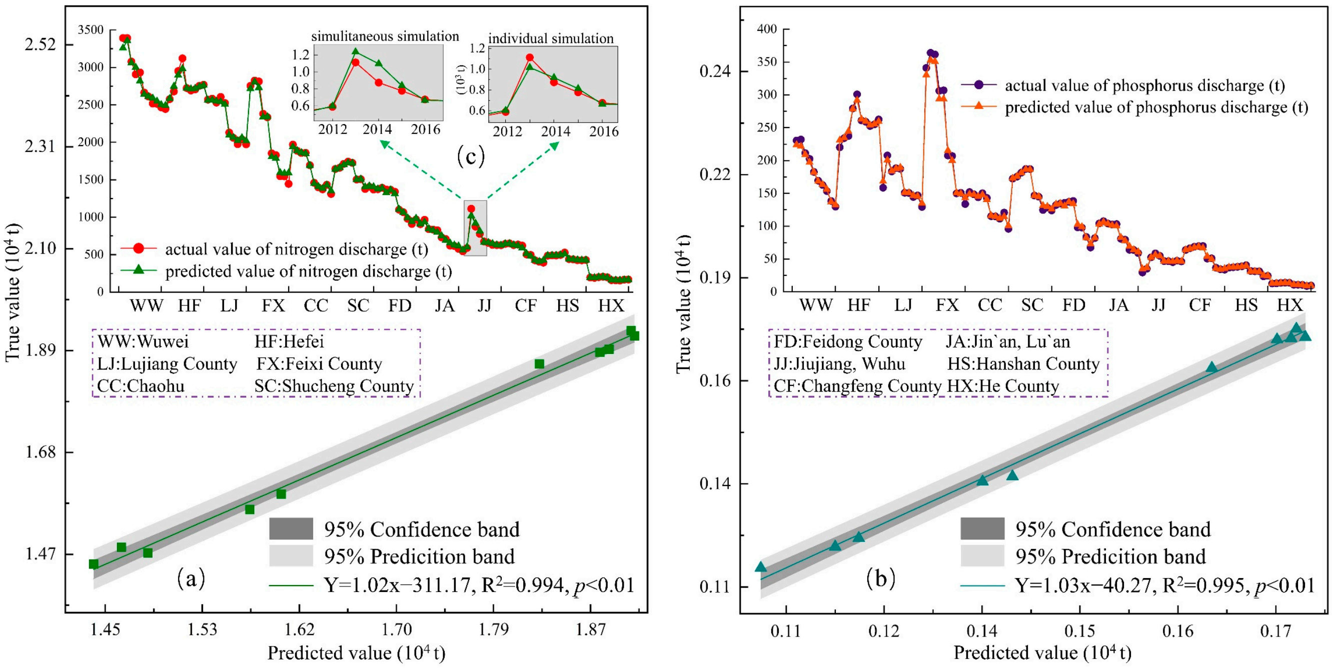

Figure 7. Simulation of N (**a**) and P (**b**) discharge in the Chaohu Lake Basin, and N and P discharge at the county level, (**c**) represents the simulated amount of N and P discharge based on whole basins (simultaneous simulation) and all individual basins (individual simulation).

The above overestimation phenomenon observed in these areas is caused by the significant difference in the contribution ratios of various pollution sources in the sub-basin and the Chaohu Lake Basin. In view of this, a separate simulation was conducted for the sub-basins of the Chaohu Lake Basin based on administrative boundaries. Through this further research, we found that separate simulations of the sub-basins of the Chaohu Lake Basin based on administrative boundaries can effectively reduce the overestimation in these areas, and it improved the accuracy of the N and P simulated contents by 3.40% (Chaohu City), 10.35% (Changfeng County), and 20.51% (Jiujiang District).

3.4. Evaluation of the N and P Discharge Reduction under Different Scenarios

The prediction results show the total amounts of N and P discharge under the multi-factor reduction effects in the basin, and they are expected to be 2000.08 t (13.97%) and 219.42 t (19.42%) lower than those in 2020, respectively (Figure 8). The dual-factor strategy was better than the single-factor one at the basin and county scale, while multi-factor collaborative management was the best strategy. Based on the prediction for the Chaohu Lake Basin in 2025, the discharge reduction effects of the multi-factor strategies were 7.03% and 10.88% higher than when using single-factor strategies, and were 3.51% and 5.44% higher than when using dual-factor strategies.

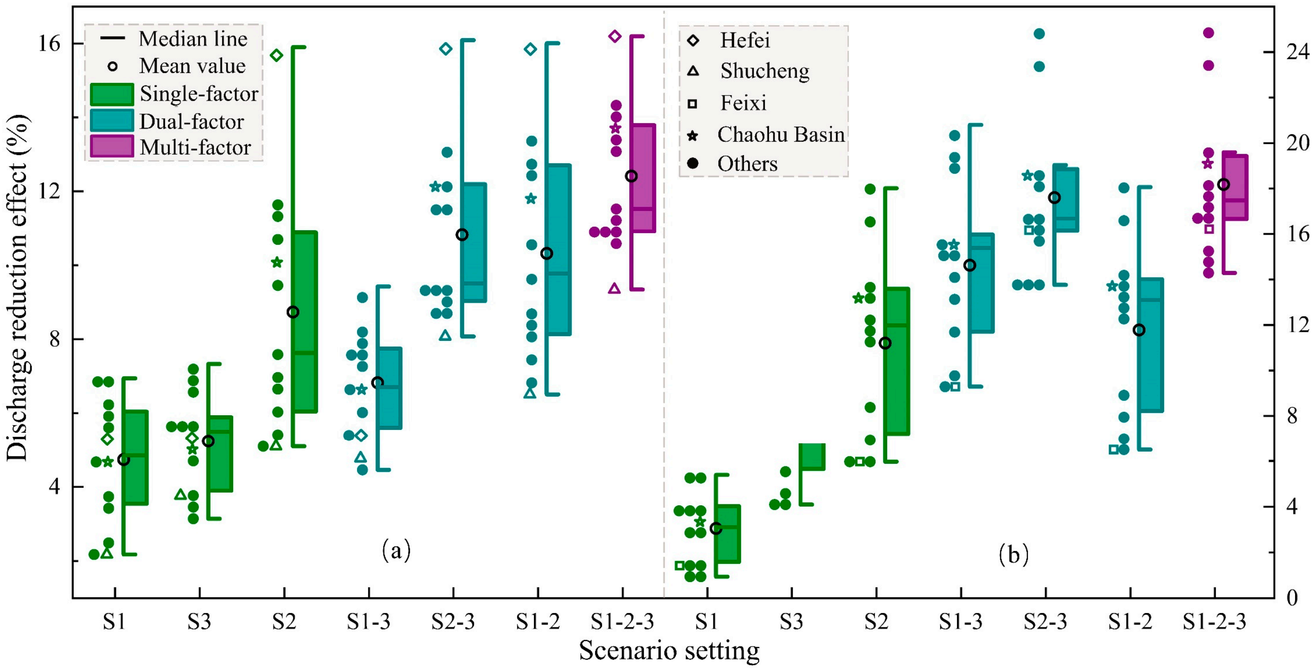

Figure 8. Production effects of N (**a**) and P (**b**) under different scenarios in 2025.

The scenario simulation results show that multi-factor measures have the best discharge reduction effect yet, as these measures demonstrated substantial regional differences. For example, under the multi-factor scenario (S1-2-3), Hefei's N discharge amount decreased by 16.20% in 2025, while that of Shucheng County only decreased by 9.34%. The key source of N discharge in Hefei is domestic sewage, and among the single factors, the abatement measures targeting domestic sewage treatment (S2) are the most effective. However, the key source of N discharge in Shucheng County is fertilizer runoff, and the abatement capacity for fertilizer runoff treatment measures (S1) is limited. In addition, the impact of the key source on the N and P discharge reduction effect also appears in the single-factor and dual-factor treatment scenarios. For instance, under the influence of dual-factor S1-2, S1-3, and S2-3, the P discharge amounts in Feixi County will be decreased by 6.50%, 11.63%, and 16.16% in 2025, respectively. Due to the difference in the contribution of each key source (contribution sources: livestock and poultry breeding > domestic sewage

> fertilizer runoff) to the P discharge, the discharge reduction effect of the dual-factor measure causes a significant difference. Therefore, the discharge reduction effects of the same treatment measures are greatly affected by the key sources in each region. Ultimately, future research on N and P treatment measures should give more attention to each region, using the multi-factor synergistic treatment measures to improve the effects of N and P discharge reduction.

4. Conclusions

Our investigations were based on the modified export coefficient method and RF model. The main conclusions of this research are as follows:

(1) Significant spatio-temporal distribution characteristics were obtained to determine the N and P discharge intensity and amount in the Chaohu Lake Basin.
(2) The key sources of N and P discharge in the whole Chaohu Lake Basin were fertilizer application, domestic sewage, and livestock breeding. Agricultural activities were the key source of N and P discharge in this area (N: 53.75%; P: 59.29%).
(3) The scenario simulation results show that the multi-factor strategy performed better than the single-factor and dual-factor ones. However, the effect of the discharge reduction measurements was different among the counties.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/agronomy13123079/s1, Table S1. Correlation analysis between rivers and N and P discharge amounts in the region.

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