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Assessing nutrient fate from terrestrial to freshwater systems using a semi-distributed model for the Fuxian Lake Basin, China

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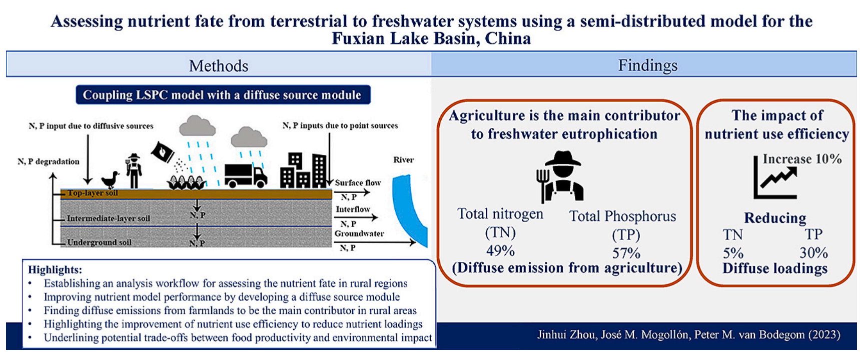
HIGHLIGHTS

- Establishing an analysis workflow for assessing the nutrient fate in rural regions
- Improving nutrient model performance by developing a diffuse source module
- Finding diffuse emissions from farmlands to be the main contributor in rural areas
- Highlighting the improvement of nutrient use efficiency to reduce nutrient loadings
- Underlining potential trade-offs between food productivity and environmental impact

GRAPHICAL ABSTRACT



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ABSTRACT

The growing and increasingly intensified agricultural sector exerts major pressures on the environment. Specifically, nitrogen (N) and phosphorus (P) runoff can induce eutrophication in freshwater ecosystems. To formulate environmental strategies for controlling eutrophication, decision-makers commonly consider the importance of pollutant contributors before developing sector-specific environmental policies. These types of science-based decisions benefit from nutrient models that quantify nutrient transport and fate. However, due to a lack of fertilizer application data, distributed models are generally not suitable for most rural regions with extensive agriculture, while lumped models cannot properly characterize the spatial variation of nutrient fate in these regions. To assess the nutrient contributions from different emission sources to freshwater, we developed a localized semi-distributed model to simulate total nitrogen (TN) and total phosphorus (TP) in 52 inflow rivers of Fuxian Lake Basin in China. The results show that diffuse sources contributed 82 % TN and 92 % TP loading to the inflow rivers. The highest eutrophication potentials (i.e., loading per area) is from the built environment, which is more than 10 times that of forests, but the contribution of the built environment to total diffuse loading is only the second-highest as it occupies 8.7 % of the surface area. Farmland is the main contributor, generating 49 % of diffuse TN and 57 % TP, respectively. Our results show that promoting a 10 % increase in nutrient use efficiency would reduce 5 % of N and 30 % of P diffuse loadings to the rivers. Through examining the impact of nutrient use efficiency, we emphasize the potential trade-offs between food productivity and environmental effects. This analysis workflow can be applied to other agricultural regions.

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1. Introduction

Nitrogen (N) and phosphorus (P) are essential nutrients for life. With the rapid development of agriculture and food production, the upsurge of anthropogenic emissions has accelerated the enrichment of nutrients. Synthetic fertilizers are increasingly used for food production (Smil, 1999; Virupax et al., 2017). Less than 50 % of nutrient application contributes to crop yield at a global scale, leading to abundant nutrient losses to the environment (Lassaletta et al., 2014). As a consequence, in recent decades these sectors have grown to become the main contributors to eutrophication in surface waters, with up to 50 % of the global nutrient contents stemming from agriculture-related sectors (Beusen et al., 2016). Agricultural production has boosted N and P losses to soils from 101 to 157 Tg yr^{-1} for total nitrogen (TN) and from 21 to 31 Tg yr^{-1} for total phosphorus (TP) between 1970 and 2000 (Bouwman et al., 2009) and this trend is likely to continue into the future with growing food demand (Mogollón et al., 2018, 2021). These nutrients have jeopardized human health in drinking water and have induced freshwater and coastal eutrophication in many regions throughout the world (Bleeker et al., 2013; Dodds and Smith, 2016; Smith et al., 2006).

The current trade-off between food production and environmental impacts due to nutrient-induced eutrophication weighs heavily on the decision process for environmental strategies. Environmental strategies commonly start with a Strategic Environmental Assessment (SEA) (Finnveden et al., 2003) to relate environmental impacts to the emission sources from different sectors. To properly couple emissions to sources from a spatial perspective, SEA requires models to regionalize nutrient fate. Nutrient models can be distinguished into lumped, semi-distributed, and distributed models according to the complexity of explicit specifications for spatial variability inside a basin (Reed et al., 2004). The lumped model is the "simplest" and requires the least spatial-specific data since it considers the whole basin as a compartment and represents the average response of physical processes over a basin (Khakbaz et al., 2012). However, nutrients stem from various natural and human sources with different economic and societal bases, and the transport of nutrients is determined by different hydrologic pathways associated with the interchange between water and soil (Seitzinger et al., 2010). Such diversity of pathways cannot be accurately described by lumped models, particularly in small-scale regions with high spatial heterogeneity, since these assume homogeneity in geographical conditions and soil characteristics (Yu, 2015). In recent years, the abundance of spatially distributed digital and remote sensing data sets, such as meteorology, elevation, and vegetation data, has facilitated the development of distributed models (Khakbaz et al., 2012). Despite the expectation that distributed models would outperform lumped models in hydrological and nutrient fate simulations, studies by Beven (1989), Grayson et al. (1992), and Reed et al. (2004) have produced mixed results, with some finding that distributed models only slightly improve, or even worsen, simulated flows when compared to lumped models (Jajarmizad et al., 2012; Khakbaz et al., 2012). This results from the difficulty of acquiring spatially explicit data with high quality and adequate quantities, especially in rural regions of low-income countries (Beven, 1989; Reed et al., 2004). Considering the significant efforts needed to parameterize and validate distributed hydrological models, as well as the mixed results of previous studies, the effectiveness of using distributed models has been questioned (Khakbaz et al., 2012).

Semi-distributed models represent a good alternative for implementing SEA in such rural regions, since it may reproduce the spatial distribution in the description of hydrological and nutrient fate in an effective way. Semi-distributed models divide a watershed into discrete subbasins and simulate the average hydrological and nutrient fluxes at the subbasin outlet using distributed properties like land use, soil type, and precipitation lumped into subbasins (Veettil et al., 2021). Unlike fully distributed models, the semi-distributed models do not incorporate routing among the smallest spatial units, known as Hydrologic Response Units (HRUs) (Kalcic et al., 2015). Thus, semi-distributed models have lower data requirements than fully distributed models that demand data for highly distributed descriptions of both spatial properties and routing between HRUs (Veettil et al., 2021). Due to data uncertainties, fully distributed models may not enhance accuracy in interior watersheds or outperform semi-distributed models when calibrating watershed variables solely at the basin outlet (Arabi et al., 2006). A well-validated semi-distributed model may accurately represent the details of nutrient flow and the contribution of different sources to eutrophication across the watershed. Semi-distributed models in environmental modeling strike a balance between lumped and fully distributed structures, allowing for some spatial variation in input data and serving as a transitional approach to capture intermediate levels of complexity (Khakbaz et al., 2012). Semi-distributed models have a weakness in the conceptualization of some parameters for physical processes (e.g., routing among spatial units) when compared to distributed models. This shortcoming may be overcome by coupling a more detailed description of key processes within the model based on the prevailing data accessibility. With such improvements, the analysis may adequately analyze nutrient flows to support environmental policies and strategies to mitigate N and P runoff from agriculture and its impact on eutrophication.

This study aims to i) improve the analysis workflow of a semi-distributed model for data-scarce agricultural regions by developing a module to enhance mechanistic descriptions of diffuse emissions and hydrological/nutrient interchange between soil layers; ii) assess the contribution of different emission sources to a freshwater system; iii) analyze the nexus between fertilizer use in crop production and eutrophication impact in the Fuxian Lake Basin. Based on the semi-distributed model Loading Simulation Program in C++ (LSPC), we developed a localized diffuse source module to analyze the impact of N and P from different sources, especially from agricultural land, in the Fuxian Lake Basin. We then calibrated and applied this model to quantify the sensitivity of changes in nutrient use efficiency. This study provides an approach for assessing the nutrient fate in remote regions where agriculture is the pillar economy. It offers insights into effectively reducing eutrophication in water quality management, which can assist strategic measures to mitigate environmental impacts of N and P application, considering potential trade-offs between food productivity and environmental impact.

2. Material and methods

2.1. Study area

The Fuxian Lake Basin represents a watershed area of 458.1 km^2 (Fig. 1), and is located between N24 ° 21′ - N24 ° 38′, and E102 ° 49′ - E102 ° 57′ (Zhang and Werner, 2009). Lake Fuxian is a drinking-water reservoir in the Yunnan province, southwest China. This deep plateau lake is surrounded by mountains and charged by 52 inlet rivers (Wang and Dou, 1998). These rivers are mostly intermittent with poor runoff regulation and fast confluence, transporting a lot of eroded soil into the lake (Wang and Dou, 1998).

The Fuxian Lake Basin is located within the subtropical monsoon climate zone, where rainfall and temperature are distinctive between the dry and wet seasons with the average annual air temperature ranging from 17 to 25 °C. Drought and cold last for winter and spring, while humid and hot conditions characterize summer and autumn (Wang and Dou, 1998). The fast seasonal changes in climatic conditions lead to uneven temporal and spatial rainfall variation across the basin. Over the 1957–2012 period, the maximal annual rainfall of 2030 mm in 2004 was more than double the minimal annual rainfall of 868 mm in 2000 (Li et al., 2016). The precipitation is also strongly influenced by topography. The northern part of the basin, notably in the Liangwang Mountain, has higher elevations and a correspondingly higher annual rainfall of 1327.9 mm, while the southern part, exemplified by Jiangchuan regions, experiences the lowest measured precipitation at an annual average of 1223.5 mm (Li et al., 2016).

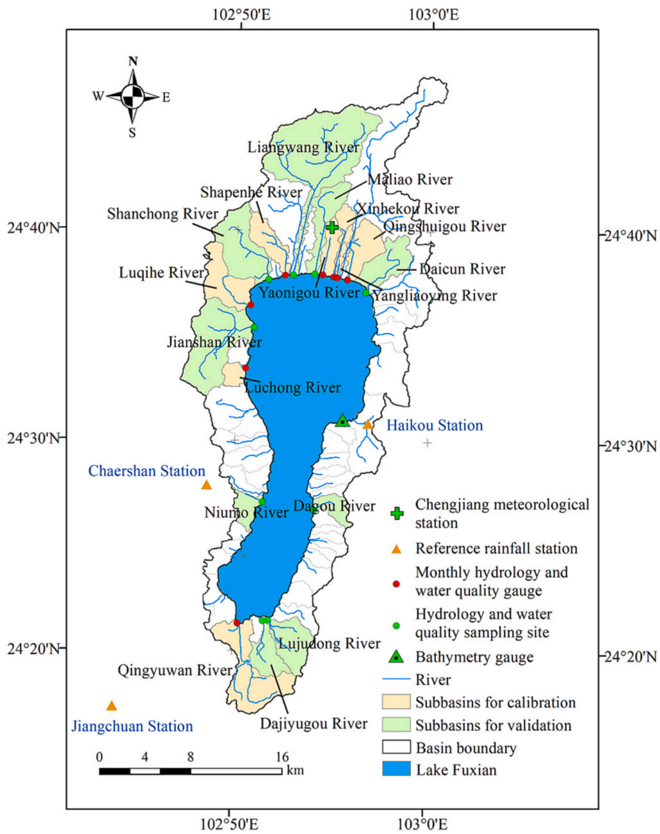

Fig. 1. Locations of meteorological, hydrological, water quality gauges and samplings, as well as the catchments of 52 rivers in Fuxian Lake Basin, China. This map highlights the subbasins of rivers for calibration and validation. Reference rainfall stations with monthly average precipitation information were employed to derive the spatial representativeness of hourly precipitation input from scaling the hourly rainfall measurements. The Chengjiang Station provides hourly meteorological measurements. Haikou Station, Chaershan Station, and Jiangchuan Station, providing monthly average precipitation information, are the reference rainfall stations.

Lake Fuxian is currently shifting from an oligotrophic to a eutrophic state due to human activities, especially due to agricultural production (Liu et al., 2009, 2014). This sector dominates the local economy as 152,100 people engage in the agricultural sector and occupy 71 % of the total population (Liu et al., 2009; Liu et al., 2014). Vegetable peas, rapeseed plants, and wheat are the main crops in autumn, while tobacco, paddy rice, and maize are the main crops cultivated in spring and summer. The farming land occupies 33.6 % of the area based on land use and land cover data (LULC). Note that here LULC is classified into 11 categories: upland field, vegetable field, paddy field, orchard, grassland, forest, built environment, road, water, hydraulic construction, and land for other uses.

2.2. Nutrient model

A site-specific SEA requires a nutrient model that describes the nutrient fate in order to reproduce the whole life cycle of nutrients from the emission to the impact. The nutrient fate is strongly variable in space and time.

In this study, we took the semi-distributed model, LSPC (version 4.3, https://catalog.data.gov/dataset/loading-simulation-program-c, (Shen et al., 2005)) as the basis for our analysis of nutrient fate in the Fuxian Lake Basin. This model is a dynamic water quality model developed by the United States Environmental Protection Agency (USEPA). It employs the Hydrologic Simulation Program – Fortran (HSPF) (Bicknell et al., 1997) algorithms to simulate water quality. Based on the geographical information (land use, soil, and topography), LSPC characterizes areas that have homogeneous responses to precipitation and other environmental factors (e.g., land use and soil type) as Hydrologic Response Units (HRUs). LSPC has the advantage of scalability, as it can handle small-to-large-scale watershed modeling with user-defined limitations based on computing resources (Yuan et al., 2020). Designed for professionals with a background in watershed modeling, LSPC is a versatile and robust tool that can assess the source contributions in various geographic areas, which matches the aim of this study. The source contributions are calculated based on emission generation rates from different land units (land types). LSPC allows users to customize various parameters for diffuse sources (e.g., the accumulation rate of nutrients) and specific details for point sources (e.g., date, type, flow rate, and concentration). LSPC simulates soil water flows, distinguished into a surface layer, an interflow layer, and a groundwater layer. Finally, the output format can be customized in a time-aggregated .csv file, either hourly, daily, monthly, or annually, including loadings, concentrations, discharge, or water volume, organized by land use or by stream segment, among other options (e.g., subbasins). LSPC can distinguish the contributions of the overall point sources and diffuse sources, but it cannot separate the specific nutrient inputs (i.e., fertilizer, manure, etc.).

LSPC simulates diffuse sources using a buildup-washoff model, similar to HSPF, but it lacks the capability to handle complex groundwater routing to describe interactions between surface water and groundwater (Yuan et al., 2020). In the nutrient modeling, LSPC considers the soil as a single-layer compartment. For watersheds with complex geographical and hydrological conditions, like the Fuxian Lake Basin, LSPC may need a more comprehensive representation of nutrient fate from the soil surface and the intricate interactions between surface water and groundwater.

To incorporate a more mechanistic description of routing and complement the lack of descriptions of nutrient exchange between soil layers in LSPC, we developed a localized diffuse source module to better represent the processes of nutrient flows from diffuse sources to the soil compartments. This module describes that nutrients (total N and total P) from diffuse sources such as fertilizer and manure used in agriculture accumulate in the top-layer soil, from which they can be absorbed by plants, attenuate (e.g., by denitrification), and potentially leach into interflow and groundwater. At each time step, the nutrient concentration in the different layers is updated depending on nutrient inputs, leaching, and degradation (e.g., N_2O denitrification, volatilization of NH_3). The degradation in each layer is expressed by a first-order equation. The localized diffuse nutrient module is described in detail in Section S2 of the supplementary material.

2.3. Data selection

The SRTM 30 m - Digital Evaluation Model - version 4.1 was used for establishing subbasins and the river network (Jarvis et al., 2008). Topography data, soil type data, and land use and land cover data were used to extract HRUs (CARD, 2013). Daily climate data were collected for the Chengjiang station from Jan. 01, 2014, to Dec. 31, 2015, including rainfall, air temperature, potential evaporation, humidity, atmospheric pressure, solar radiation, and wind speed. Due to strong temporal-spatial variations in meteorological data, one gauge was insufficient to reproduce the spatial characteristics of the Fuxian Lake Basin, especially precipitation data. Rain gauge networks that are spatially well-distributed in the watershed would reduce the errors in hydrological predictions (Lee et al., 2018). When the gauge networks are sparse, a widely used solution is employing gauges close to the basin to represent the spatial variation in rainfall characteristics (Kalin and Hantush, 2006; Tuo et al., 2016). However, networks for other meteorological data were not available. We, therefore, produced hourly precipitation data for the Haikou Station, Chaershan Station, and Jiangchuan Station (shown as reference rainfall stations in Fig. 1) based on their monthly average rainfall from 1957 to 2012 (Li et al., 2016) and the hourly precipitation records of Chengjiang Station. We applied Thiessen polygons to distribute the scaled precipitation data for these three reference stations. Although uncertainties in precipitation estimates cannot be fully avoided due to a lack of real-time precipitation data for multiple stations, Thiessen polygons can improve the representativeness of rainfall on undesirable distributions of observational networks (Anctil et al., 2006; Barbalho et al., 2014). The descriptions of input data can be found in Table S1 of the supplementary material.

Discharge and nutrient concentration data were collected from a network of measurement gauges, including the manual sampling of discharge, TN, and TP concentration (hourly, only measured during rainstorms) in 9 rivers, monthly TN and TP concentration measurements in 8 rivers, daily observed discharge in Xinhekou River, and a daily bathymetry measurement. An overview of geographic, emission, and measurement data used in this study is shown in Fig. 1 and Table S1 of the supplementary material. There is no measurement in reservoirs or information on dams.

To represent the spatial distribution of geographical and hydrological conditions, we divided the nutrient model of the Fuxian Lake Basin into 142 subbasins with 5 reservoirs and 52 rivers. We furthermore evaluated the model using an hourly time step. By creating small-scale categories, we avoided some of the complications of parameterizing a fully distributed model while capturing the spatial distribution of nutrient fate across the basin. Based on LULC, soil type, and slope information, we classified 44 HRUs in the model to represent the orographic and geographical variation. The hydrology and nutrient fate of rivers were simulated from Jul. 01, 2014, to Jun. 30, 2015.

According to the report for water environment protection and treatment in Fuxian Lake Basin in 2015 (RWEP, 2015), the point source emissions of TN and TP were 281.3 t yr^{-1} and 8.53 t yr^{-1}. Due to a lack of temporal and spatial data, point sources including mining, industrial, and urban domestic sewage were set to evenly emit at each time step, while hotel emissions were assumed to be three-fold higher in the tourism season (from March to August) compared to the tourism off-season (from August to February). The spatial distribution was determined by the geographical distribution of the corresponding sectors.

We used the bathymetry of Lake Fuxian and the annual inflow against rainfall observations to calibrate the hydrological parameters. The daily discharge of Xinhekou River and the measurements of the discharge of 9 rivers were collected to validate hydrology during rainstorm periods (including Jianshan River, Shanchong River, Liangwang River, Maliao River, Daicun River, Dagou River, Lujudong River, Dajiyu River, and Niumo River). The TN and TP concentrations of 8 rivers observed monthly (including Xinhekou River, Qingshuigou River, Yangliaoying River, Shapenhe River, Luqihe River, Yaonigou River, Qingyuwan River, and Luchong River) were employed to calibrate the nutrient fate modeling. The measurements of TN and TP concentration in 9 rivers during rainstorm periods and the annual export loadings to Lake Fuxian were used for validation of the nutrient fate modeling. The calibrated and validated subbasins are shown in Fig. 1 and the results can be found in Section 3.1 of the manuscript and Section S3 of the supplementary material.

2.4. Agricultural nutrient balances

N and P balance ($N_{balance}$ and $P_{balance}$) represent the net change in N and P based on the difference between their input and their removal at the soil surface. The N and P balance was estimated for the HRUs of the calibrated LSPC. N and P from soil release due to long-term accumulation of nutrients ($N_{soil\ release}$ and $P_{soil\ release}$) were deduced by using Eq. 1 and Eq. 2, since other variables were known or derived from data. According to the local agriculture bureau surveys, fertilizer application in Fuxian Lake Basin is 10,500 tN yr^{-1} and 2400 tP yr^{-1}, which accounts for the N and P input from fertilizer ($N_{fertilizer}$ and $P_{fertilizer}$). The survey also provided the amount of fertilizer application on different farmland types based on the cultivated crops. The N and P emissions from rural wastewater ($N_{waste,rural}$ and $P_{waste,rural}$) and manure (N_{manure} and P_{manure}) were obtained by multiplying nutrient emission coefficients (i.e., emission per capita per day) (Ministry of Ecology and Environment of the People's Republic of China, 2021a, 2021b) with population and livestock, respectively. Note that rural wastewater and manure were accounted for as diffuse emissions since sewage treatments had not been established for the rural region of Fuxian Lake Basin in 2015. N and P removal by crop harvest (N_{crop} and P_{crop}) were derived by multiplying the annual agricultural production by the N and P content in plants (N% and P% in plants) (Greenwood, 1982; Sandana and Pinochet, 2014). As Greenwood (1982) as well as Sandana and Pinochet (2014) provided ranges of N% and P%, we applied the mean values of the recommended ranges. N fixation ($N_{fixation}$) was calculated by multiplying the farmland area by the N fixation per area in China (Gu et al., 2015). N fixation on farmland includes natural biological N fixation (NBNF, 0.74 tN/km^2) and cultivated biological N fixation (CBNF, 0.48 tN/km^2) (Gu et al., 2015).

$$N_{balance} = N_{fixation} + N_{fertilizer} + N_{waste,rural} + N_{manure} + N_{soil\ release} - N_{crop} \tag{1}$$

$$P_{balance} = P_{fertilizer} + P_{waste,rural} + P_{manure} + P_{soil\ release} - P_{crop} \tag{2}$$

2.5. Sensitivity and uncertainty analysis of nutrient use efficiency

The nutrient use efficiency is defined as the ratio between agricultural production and fertilizer application. In this study, we approximate the crop harvest as the agricultural production, similar to the common practice in other studies. Due to a lack of knowledge on how to effectively avoid yield gaps, farmers currently use excessive nutrient supply. We conducted a sensitivity analysis of nutrient use efficiency assuming that the crop harvest remains unchanged, while reducing unnecessary fertilizer inputs, consequently increasing nutrient use efficiency. Since the effect of change in nutrient use efficiency on other inputs of nutrients (e.g., soil release) is long-term and unknown, we set these inputs unchanged during the sensitivity analysis.

Current N use efficiency (NUE) and P use efficiency (PUE) were calculated by Eq. (3) and Eq. (4) respectively:

$$NUE = \frac{N_{crop}}{N_{fertilizer}} \tag{3}$$

$$PUE = \frac{P_{crop}}{P_{fertilizer}} \tag{4}$$

According to the experiments of Greenwood (1982) as well as Sandana and Pinochet (2014), the nitrogen content in plants (N%) ranges from 3.56 to 4.00 and phosphorus content in plants (P%) ranges from 0.11 to 0.27. This may lead to an uncertainty in the estimates of N_{crop} and P_{crop}. We therefore applied the upper and lower bounds of the ranges to estimate the uncertainty in the sensitivity analysis. Eventually, we provide the relationship between the reduction in diffuse loading and the increase in nutrient use efficiency for the current model (on the basis of mean values of N% and P%) and the uncertainty ranges.

3. Results and discussion

3.1. Assessing N and P loading

The evaluation of watershed model performance involved a comprehensive analysis including graphical comparisons and statistical metrics to evaluate the accurate reproduction of observations, following the method for evaluating the model performance of Duda et al. (2012). For the simulations where continuous observations were available, both techniques were used, while for discrete observations, graphical comparisons were considered applicable (Duda et al., 2012). In this study, the calibration and validation show that our model has a good

Table 1
Total nutrient loading to 52 rivers and nutrient export into Lake Fuxian (unit of tN yr^{-1} for total nitrogen (TN) and tP yr^{-1} for total phosphorus (TP)). The proportion of nutrient loadings from diffuse and point source, and nutrient export were calculated by dividing their amount by the total loading into the rivers.

	TN (tN yr^{-1})	TP (tP yr^{-1})	TN (%)	TP (%)
Nutrient export into the lake	1386.9	93.6	99.5 %	99.8 %
Loading from diffuse sources	1147.3	85.9	82.3 %	91.6 %
Loading from point sources	246.0	7.9	17.7 %	8.4 %
Loading into river system	1393.3	93.8	100 %	100 %

performance in the Fuxian Lake Basin. The Nash-Sutcliffe Efficiency (NSE) of the water level in Lake Fuxian is 0.79 and the NSE of Xinhekou River is 0.89. For the discrete samples of hydrology and nutrients, the simulations in most rivers display a good match with observations from the graphical comparisons (details can be found in Section S3 of the supplementary material).

Diffuse sources represent the main contributor to riverine TN and TP loadings, providing 82 % of TN and 92 % of TP (Table 1). This result is in line with the perspective of Fang (1999) that diffuse sources dominate the pollution of the Fuxian Lake Basin.

Low N and P retention (0.5 % TN and 0.2 % TP) occur during the transport to the lake (Table 1) due to the short rivers and the fast-response runoff in mountainous regions. Our results show that the total nutrient export from 52 rivers to Lake Fuxian are 1386.9 tN yr^{-1}, and 93.6 tP yr^{-1}. Sun et al. (2015) estimated the annual average export to Lake Fuxian from 2010 to 2015 as 901.14 tN yr^{-1}, and 112.41 tP yr^{-1}, while RWEP (2015) counted the average export of 2014 to be 1276.7 tN yr^{-1} and 74.0 tP yr^{-1}. Our simulation of TN is higher than the estimation of Sun et al. (2015) and RWEP (2015), which may result from the increase in N emissions over time. Our TP simulation falls within these estimates, with TP loading simulated by Sun et al. (2015) being the highest. Since a part of P was retained in the soil compartment in an insoluble form, P fate is more uncertain than that of N.

The hotspots of nutrient loadings are found in the population-dense regions and farmlands (Fig. 2). The downtown of Chengjiang County and Jiangchuan County are located in the north and south of Fuxian Lake Basin, respectively, surrounded by farmlands. In these subbasins, nutrient loading per area is the highest. The upstream subbasins generate less nutrients because they are occupied by natural lands (e.g., mountain forests and grassland).

The highest N and P loading per area originates from roads (9.82 tN km^{-2} yr^{-1} and 0.79 tP km^{-2} yr^{-1}, Table 2). The built environment is the

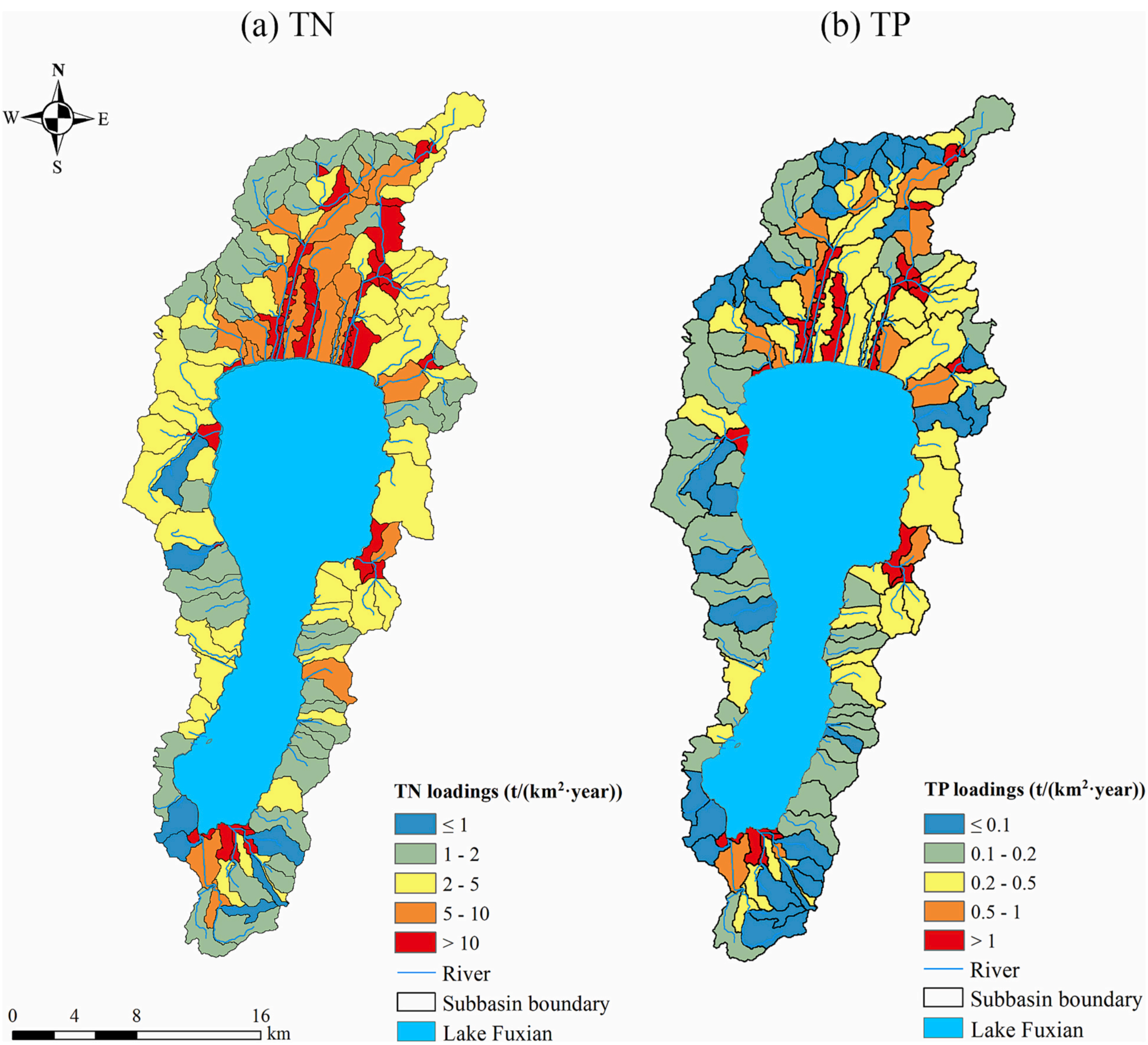

Fig. 2. The spatial pattern of nutrient loadings per area in 142 subbasins of Fuxian Lake Basin.

Table 2
Nutrient loading from diffuse sources on different land use types. This table listed the area (%), the proportion of total diffuse loading (%), the amount of diffuse loading (t), and the diffuse loading per area (t km^{-2} yr^{-1}) from 11 types of land use. The average diffuse loading per area was derived by dividing the total diffuse loading by the basin area.

	Area (%)	Proportion of Nutrient loading (%)		Nutrient loading (t yr^{-1})		Nutrient loading per area (t km^{-2} yr^{-1})	
		TN	TP	TN	TP	TN	TP
Upland vegetable cropland	23.7 %	36.4 %	44.8 %	418.0	38.5	3.85	0.36
Irrigable vegetable cropland	8.3 %	10.7 %	9.4 %	122.7	8.1	3.22	0.21
Paddy field	1.6 %	1.3 %	1.4 %	15.2	1.2	2.14	0.17
Orchard	1.1 %	0.7 %	1.5 %	8.5	1.3	1.74	0.27
Grassland	9.9 %	3.9 %	1.7 %	44.8	1.5	0.98	0.03
Forest	44.3 %	13.7 %	7.2 %	157.2	6.2	0.78	0.03
Hydraulic structure	0.1 %	0.1 %	0.0 %	0.6	0.0	1.14	0.05
Built environment	7.2 %	26.7 %	27.0 %	306.0	23.2	9.24	0.7
Road	1.5 %	5.8 %	6.3 %	66.7	5.4	9.82	0.79
Water	0.7 %	0.1 %	0.2 %	0.8	0.2	0.24	0.06
Land for other use	1.6 %	0.6 %	0.4 %	6.7	0.3	0.92	0.04
Average	/	/	/	/	/	2.5	0.19

second highest emitter per area (9.24 tN km^{-2} yr^{-1} and 0.70 tP km^{-2} yr^{-1}, Table 2), which is more than 10 times that of forests. This agrees with the conclusion that urban diffuse pollution due to runoff from roads, houses, and commercial areas contributes the most to the eutrophication potential (Phillips et al., 2018). However, the diffuse loading contribution of roads and built environment is secondary to farmlands, since roads and the built environment only occupy 8.7 % of the basin area. Farmland including upland and irrigable vegetable cropland, paddy field, and orchards is the dominant land use and contributes 49 % TN and 57 % TP of the total diffuse loading (Table 2). This result is in line with the estimation of 50 % of nutrient exports from agricultural sectors by Beusen et al. (2016). Our findings that agricultural land and construction land (i.e., road and built environment) have more detrimental impacts on eutrophication in the water environment than forests are consistent with Cheng et al. (2022) and Pistocchi (2020). The main diffuse sources are uncollected wastewater and fast runoff on construction land and excessive nutrients due to fertilizer application on agricultural land.

The upland field for vegetables is the dominant land use and contributes 36 % TN and 45 % TP of the total diffuse loading (Table 2). It generates the highest loading per area for N and P among the farmlands since frequent rotations of vegetables require more fertilizer than other crops (RWEP, 2015). Orchards for fruit trees generate more TP loading per area than irrigable fields and paddy fields while this is not the case for N. Farmers tend to apply excessive P fertilizers in orchards, because fruit trees require more P fertilizer than paddy rice, maize, and grains.

3.2. Contributions to N and P emissions due to agriculture

The hotspots of N and P balances are distributed in the north and south of Fuxian Lake Basin because of intensive agricultural activities (Fig. 3). Due to fertilizer applications, the N balance and the P balance on farmland can be 10 times and 40 times that of natural areas such as grassland, respectively.

During the modeling period, N and P balances due to agriculture were estimated as 11,527.5 tN yr^{-1} and 2462.8 tP yr^{-1}, respectively, based on the calibration of the model (Fig. 4). Fertilizer provides 71 % and 93 % of the N and P inputs, respectively, being the largest contributor to diffuse sources from farmlands. N input from soil release contributes 28 %, which is much higher than the 7 % for P, due to the differences between the N and P cycle. N has a variety of redox forms and actively exchanges with soil and water, while a major portion of P occurs in solid and inactive forms (Toth et al., 2006).

Current NUE and PUE values are 31.5 % (= 3312.4 tN crop/ 10,500 tN fertilizer, Fig. 4 (a)) and 6.9 % (= 166.4 tP crop/ 2400 tP fertilizer, Fig. 4 (b)), respectively, which is much lower than the world average (NUE of 50 % and PUE of 15 %–25 % on average) (Dhillon et al., 2017; Govindasamy et al., 2023). However, due to a historical lack of proper nutrient management policies, nutrient use efficiency in China is lower than the global average. Our estimation of NUE is higher than the average of Yunan province (26 %–30 %) (Ma et al., 2012), while our PUE is still lower than the average PUE of China (11 %–13 %) (Wang et al., 2011). In our study, we used the overall N and P content in entire plants (N% and P% in plants), while other studies (e.g., (Sandana and Pinochet, 2014)) used N and P contents of the aboveground biomass, which is usually higher. This may have led to lower NUE and PUE estimates. Considering the uncertainty of N% and P%, the current NUE ranges from 29.7 % to 33.4 %, while PUE ranges from 4.0 % to 9.9 %, which approximates the level of China. In conclusion, the low nutrient efficiency and excessive fertilizer application are the main culprits for the eutrophication of the Fuxian Lake Basin.

3.3. Sensitivity of nutrient balances to increased nutrient use efficiency

The local agricultural bureau has taken actions to curb the deterioration of local water quality. They currently request local farmers to use advanced techniques of fertilizer application and switch from a traditionally intensive rotation to a combination of fallow and improved forms of agriculture management (RWEP, 2015). These actions release farmland pressures on the environment by means of planting fewer crops/vegetables and promoting nutrient use efficiency.

We simulated the reduction of diffuse loadings under improving rates of NUE and PUE (Fig. 5). The results show that improving the nutrient use efficiency causes more reduction in TP loadings than in TN loadings compared to the current nutrient loading. The reason mainly exists in that 1) P fertilizer represents 97 % of the P balance vs. 91 % for N, and 2) the current PUE is 6.9 %, which is substantially lower than the current NUE of 31.5 %. Consequently, improving PUE can lead to a greater reduction of P vs N emissions. For instance, if we assume the crop production and soil release to remain unchanged and promote 10 % NUE and PUE (i.e. if we are able to break the current trade-off between food production and nutrient emissions), our model shows that TN and TP export to Fuxian Lake is 1328.7 tN yr^{-1} and 68.1 tP yr^{-1}, respectively, which reduces 5 % N and 30 % P diffuse loading to the rivers. The effect of improving PUE has more uncertainty due to a wider range of P%: considering the uncertainty of N% and P%, the reduction in diffuse loading ranges from 4.9 % - 5.3 % for N, and 25.5 % -33.0 % for P (Fig. 5). Such maximization of PUE and NUE needs much effort in optimizing local agronomy practices and breeding nutrient-efficient crop cultivars (Ebbisa, 2022). In particular, improving PUE is much harder since the complexity of PUE arises from the multifaceted functional and structural roles that P serves in plants (Bovill et al., 2013). If promoting nutrient use efficiency is set to be a long-term strategy, N and P soil losses will decrease, and thus the reduction of N and P loadings may be even higher than our estimations.

We compared the nutrient loading to the rivers in 142 subbasins when promoting nutrient use efficiency with the current state (Table S2 in the supplementary materials). When promoting nutrient use efficiency, the nutrient loadings that are generated per area are reduced in all subbasins.

3.4. Implications for nutrient modeling and limitations

Nutrient modeling studies typically deal with uncertainties, which pertain to data availability for model input and for calibration and

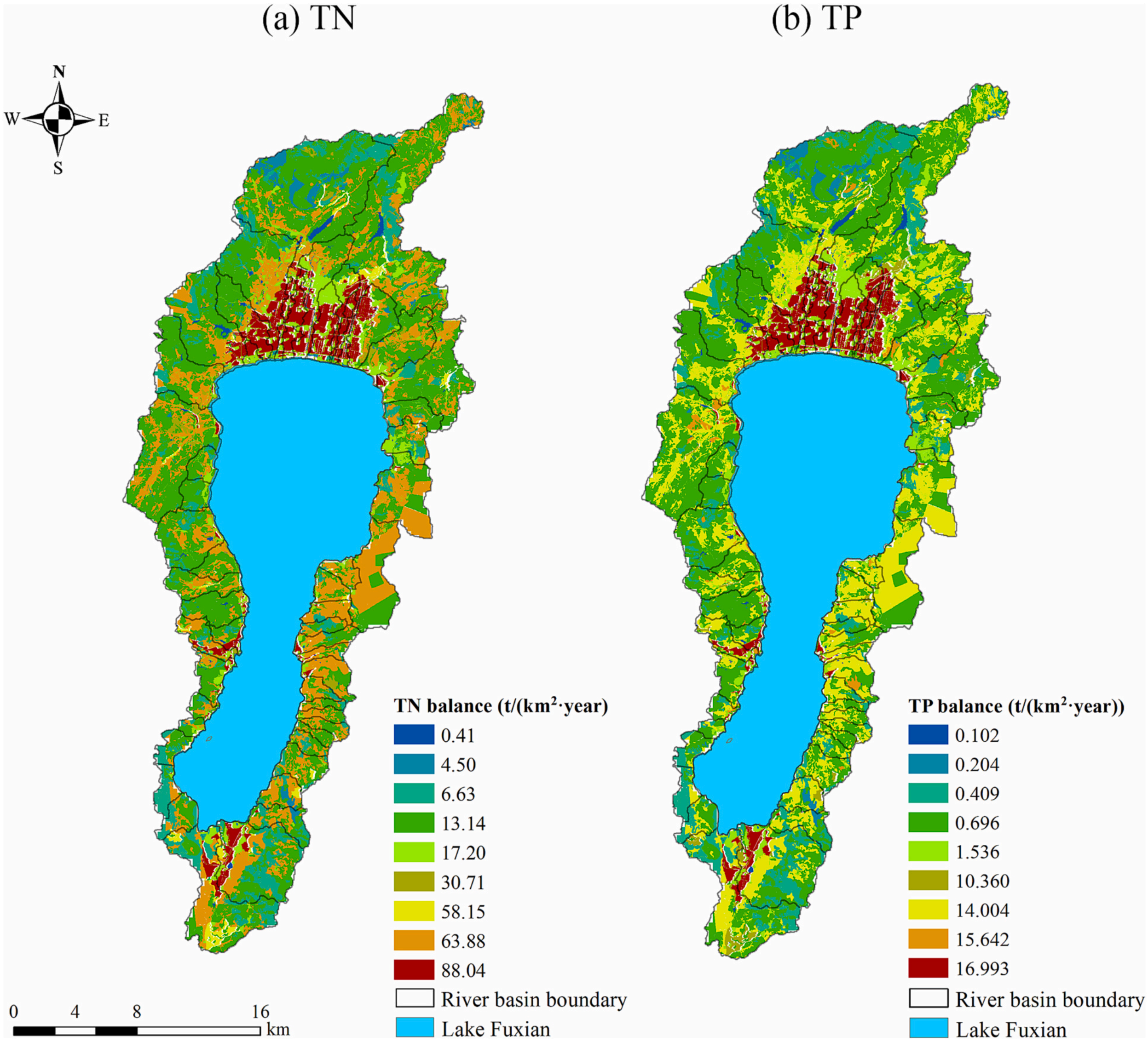

Fig. 3. The spatial pattern of nutrient balance in hydrological response units (HRUs).

validation, as well as model capability to reproduce reality. In this study, we have a certain amount of data that is qualified for modeling and validating, such as a rainfall gauge with continuous hourly observations, hydrological measurements in 18 rivers and the lake, and nutrient measurements in 17 rivers. However, these data are not able to fully reflect spatial-temporal variations because the observed discharge and nutrient concentration data were measured only on a monthly basis and during rainstorm events whilst not covering all 52 rivers. Besides, the lack of reservoir information might induce an underestimation of discharge and overestimation of TN and TP concentrations in the rivers (e.g., Liangwanghe River, in section S3 of the supplementary material), since reservoirs supply irrigation water for the downstream farmlands. The lack of climate data may have caused an underestimation of discharge in Lujudong River, Dajiyu River, and Niumo River (section S3.1 of the supplementary material).

The data was collected in 2014 and 2015 and we do not have access to later data. Recently, the local administration established wetlands at the river mouth, pipelines for rural wastewater, and more water treatment plants. These engineering constructions can filter part of the nutrients from upstream regions and reduce nutrient loadings to Lake Fuxian. Our model does not include this new infrastructure. Future modeling work should incorporate the impact of these effects to assess the nutrient cycling effects of these improved management practices.

For many rural areas throughout the world, such a lack of data is always a weak point for hydrological and nutrient modeling, and thus the choice of model is quite important (Xue et al., 2022). Although lumped models may require fewer data, lumped models cannot represent spatialized nutrient fate within the basin as that demands assessing site-specific impacts of N and P. Semi-distributed models have the advantage of a lighter data requirement than fully distributed models while still reflecting the spatial variation. In our study, we showed that LSPC coupled with our localized diffuse source module can outperform in the data-scarce regions: the calibration, validation, and consistency between our results and other studies reveal that our semi-distributed model can effectively reflect the nutrient impact. Our work innovates semi-distributed model development by enhancing the characterization of nutrient transport processes and by optimizing the use of localized data.

For future work, if more climate, reservoir, and biogeochemistry data are available, a more process-based model (e.g., The Soil & Water Assessment Tool (SWAT) (Arnold et al., 2012)) or a fully distributed model (e.g., the Integrated Model to Assess the Global Environment-Dynamic Global Nutrient Model (IMAGE-DGNM) (Vilmin et al., 2020)), can be applied. These models have more complexity than

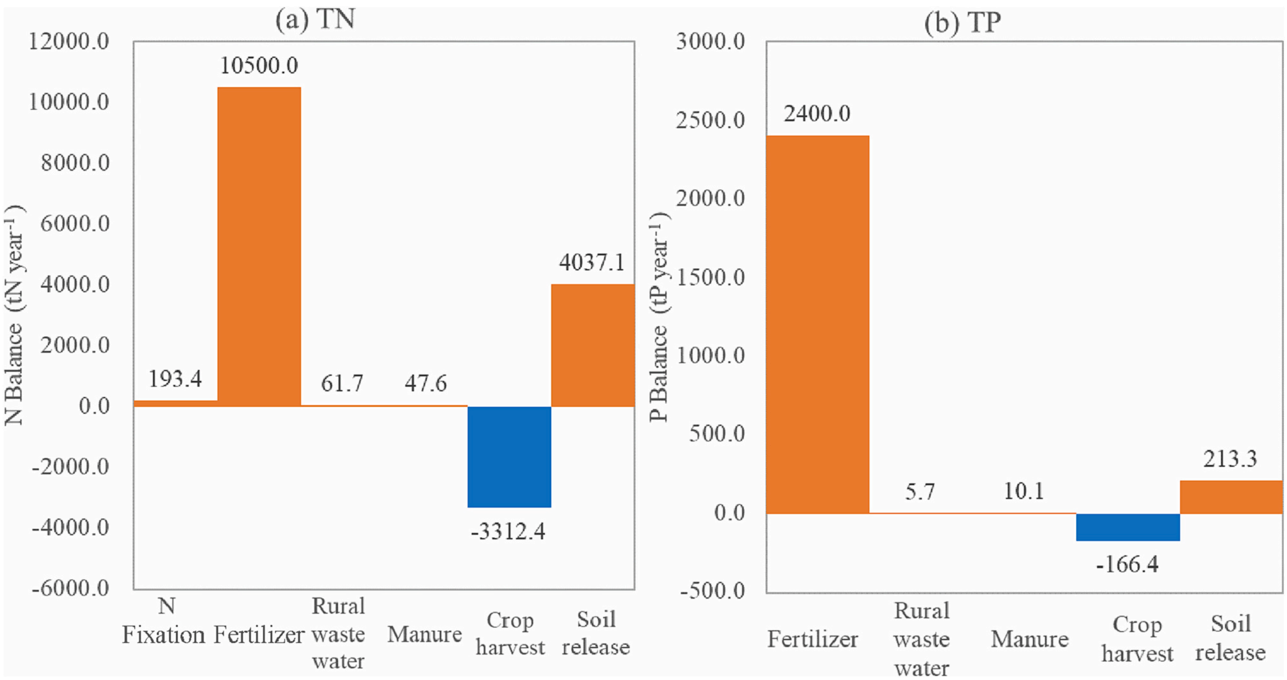

Fig. 4. The total nutrient balance on farmlands: (a) total nitrogen (TN) and (b) total phosphorus (TP). The method of calculating the nutrient inputs can be found in Section 2.4.

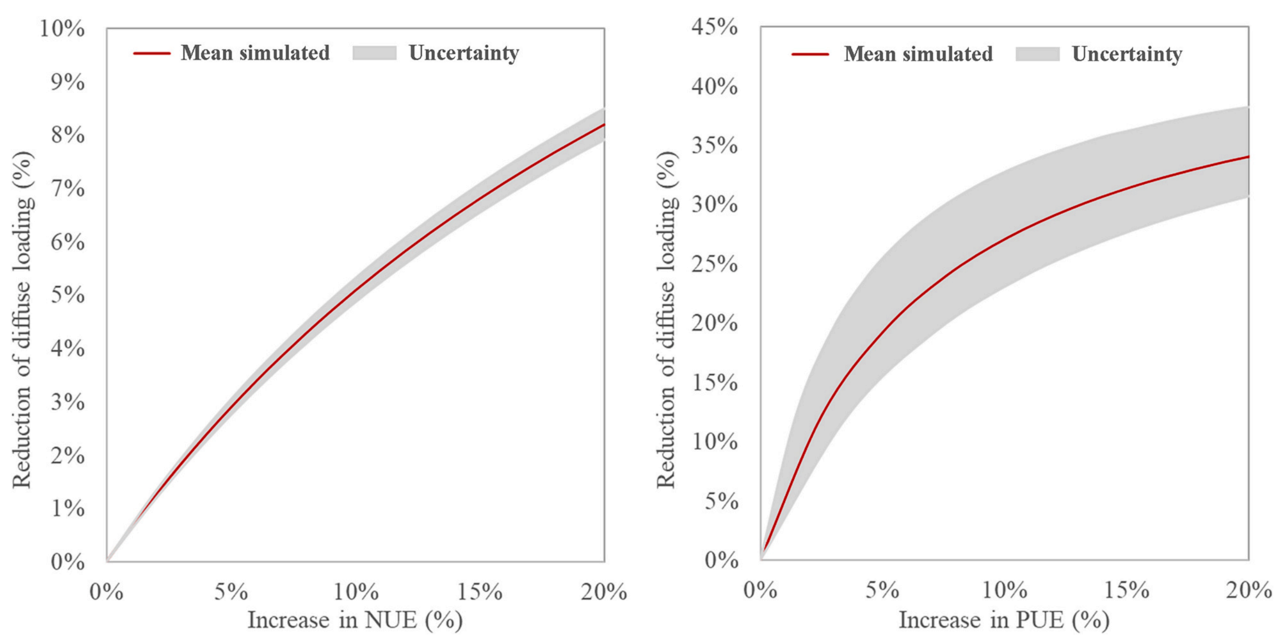

Fig. 5. The reduction of total diffuse loading due to the increase in nitrogen use efficiency (NUE) and phosphorus use efficiency (PUE). The sensitivity analysis of nutrient use efficiency was conducted by assuming the crop harvest remains unchanged, while excessive fertilizer applications can be reduced with an increase in nutrient use efficiency. Other inputs were set unchanged during the sensitivity analysis. The uncertainty was analyzed by considering the range of dry-matter nutrient content in crops: N% ranged from 3.564 to 4.0 and P% ranged from 0.11 to 0.27. The details of the method can be found in Section 2.5.

current semi-distributed models, and provide predictions of nutrient species (e.g., nitrate, ammonium, phosphate) with a finer spatial resolution. SWAT simulates the nutrient balance in a process-based way and can improve the representativeness of orographic variation of nutrient species using more regionalized HRUs. IMAGE-DGNM captures process-based biogeochemistry such as redox reactions of nutrients in surface freshwater at a grid-cell scale. However, the increased complexity and size of the model might lead to increased uncertainty and the need for more parameterization, which would highly rely on data availability including water transfers, return flows, the pumping of groundwater, and biochemical features of soils (Stern et al., 2016). Thus, as long as input data is not improved, our approach of developing semi-distributed models may provide the best compromise.

As a sensitivity analysis, we examined the impact of promoting nutrient use efficiency in an attempt to break the potential trade-off between food productivity and environmental effects in water quality management. Such promotion of nutrient use efficiencies allows for substantially reducing diffuse nutrient loading, particularly of P.

Evaluating the differential responses of different nutrients to such practices is another advantage of our workflow. This analysis can be applied to other agricultural regions with extensive agricultural practices and provide support for SEA in these regions.

4. Conclusions

This study focused on the Fuxian Lake Basin, assessing the impact of N and P on freshwater systems in rural areas. Our findings highlighted current agricultural applications, especially with low-efficiency fertilizer use, as the primary source of freshwater eutrophication. Using the semi-distributed model LSPC, we identified the temporal and spatial variations of N and P loadings from various sources. The model was optimized for performance by coupling a newly developed diffuse source module with LSPC and maximizing the use of input data. Our analysis emphasized a trade-off between food productivity and environmental impact by quantifying the mitigation of the eutrophication impact when promoting increased nutrient use efficiencies against a background of excessive use of nutrients in agriculture. Overall, this study provides an approach for managing nutrient fate in rural regions, aiding in water quality assessment, and supporting environmental strategies to deal with the trade-off between food production and the environment in agricultural regions.

CRediT authorship contribution statement

Jinhui Zhou: Writing – review & editing, Writing – original draft, Visualization, Methodology, Formal analysis, Data curation, Conceptualization. **José M. Mogollón:** Writing – review & editing, Writing – original draft, Supervision, Methodology, Conceptualization. **Peter M. van Bodegom:** Writing – review & editing, Writing – original draft, Supervision, Methodology, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Due to the confidential policy of the local government, raw data is limited for the use of this project. Data from the meteorological, hydrological, and water quality stations in this study cannot be shared. The data used in this study are listed in section S1 of the supplementary material.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.scitotenv.2024.171068.

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