Terrestrial nutrient exports and environmental changes explain eutrophication trends in fifty large lakes of Yangtze Plain, China

Qi Guan

School of Environmental Science and Engineering, Southern University of Science and Technology, Shenzhen, Guangdong, China.

Jing Tang

Department of Physical Geography and Ecosystem Science, Lund University, Lund, Sweden.

Lian Feng (✉ fengl@sustech.edu.cn)

School of Environmental Science and Engineering, Southern University of Science and Technology, Shenzhen, Guangdong, China.

Stefan Olin

Department of Physical Geography and Ecosystem Science, Lund University, Lund, Sweden.

Guy Schurgers

Department of Geosciences and Natural Resource Management, University of Copenhagen, Copenhagen, Denmark.

Research Article

Keywords: Eutrophication, LPJ-GUESS, Terrestrial nutrient exports, Fertilizer, Yangtze Plain

Posted Date: January 25th, 2022

DOI: <https://doi.org/10.21203/rs.3.rs-1280737/v1>

License: © ⓘ This work is licensed under a Creative Commons Attribution 4.0 International License.

[Read Full License](#)

Terrestrial nutrient exports and environmental changes explain eutrophication trends in fifty large lakes of Yangtze Plain, China

Qi Guan^{a, b}, Jing Tang^{c, d}, Lian Feng^{a, *}, Stefan Olin^c, Guy Schurgers^b

^a School of Environmental Science and Engineering, Southern University of Science and Technology, Shenzhen 518055, Guangdong, China.

^b Department of Geosciences and Natural Resource Management, University of Copenhagen, Copenhagen, Denmark.

^c Department of Physical Geography and Ecosystem Science, Lund University, Lund, Sweden.

^d Department of Biology, University of Copenhagen, Copenhagen, Denmark.

* corresponding author: fengl@sustech.edu.cn

Abstract

Over the past two decades, lakes in Yangtze Plain have suffered from serious eutrophication, in some regions with increased frequency of cyanobacteria blooms over years. In this study, we investigated the underlying causes of eutrophication using a combination of process-based ecosystem modelling and statistical data analysis. We found that terrestrial nutrient exports with runoff have significantly increased from 1979 to 2018 in Yangtze Plain, directly linked to the enhanced usage of chemical fertilizer for crops. Based on statistical analyses of environmental variables, terrestrial nutrient exports and satellite-observed probability of eutrophication occurrence (PEO), we separated the studied fifty lakes into five classes with similarities in environmental and nutrient variations, and attributed key factors in controlling the temporal changes of PEO. The results showed that the satellite-observed PEO trends in five classes could be largely linked to the terrestrial nutrient exports and environmental changes. Specifically, we found agricultural activities can explain the observed eutrophication trends in western lakes where lake catchments are dominated with arable and natural land, and the reduced discharge of industrial wastewater was found to be linked to the declining trends in eutrophication for eastern lakes where the green growth of industrialization were promoted from 2003 to 2011. These findings highlight the importance of sustainable management of agriculture and industrialization to overcome eutrophication issues in this region.

Keywords: Eutrophication, LPJ-GUESS, Terrestrial nutrient exports, Fertilizer, Yangtze Plain

1. Introduction

Eutrophication in the Earth's surface waters has become a global environmental concern (Sinha et al. 2017), which

has been mainly linked to nutrient over-enrichment, mainly nitrogen (N) and phosphorus (P) elements because they can greatly accelerate phytoplankton growth and development (Beman et al. 2005; Gooddy et al. 2016). Concurrent with eutrophication, algal blooms are demonstrated to occur at high intensity and frequency globally (Schindler et al. 2008; Wilhelm et al. 2011), which have resulted in negative impacts on ecological, societal and economic systems, such as water quality deterioration, biological habitat damages and freshwater resource shortage (Guan et al. 2020; Lewis et al. 2011). Cyanobacteria can be able to release toxic substances for competing light and survival resources with other phytoplankton, which, however, poisons water bodies, especially inland lakes and reservoirs to threaten water availability as drinking water sources and destroy food chains in aquatic ecosystems (Paerl et al. 2011; Zhao et al. 2019).

As a typical example of human-environment interaction, Yangtze Plain also witnessed frequent eutrophication under great anthropogenic stresses (Hong et al. 2021; Liu et al. 2020). Analysis based on satellite imagery has found that severe eutrophication has largely changed water environments in most lakes on the Yangtze Plain (Guan et al. 2020; Ma et al. 2010). Frequent cyanobacteria blooms polluted water quality in Taihu and Chaohu Lake and threatened drinking water safety for millions of citizen in local cities (Guo 2007; Huang et al. 2019; Shi et al. 2015). Although local governments have made great efforts to monitor and control eutrophication (Xu et al. 2015), cyanobacteria blooms still occur at increased frequency, indicating that there are missing processes and/or unquantified nutrient sources at landscape scale.

Many previous studies have attempted to track the causes of eutrophication on the Yangtze Plain at the level of individual lake, such as in Taihu and Chaohu (Huang et al. 2020; Zou et al. 2020). Wang et al. (2019b) distinguished that diffuse nitrogen sources from agricultural and urban systems contributed 90% to river nitrogen exports, while point sources contributed 52% to river phosphorus exports in Taihu Lake based on in-situ measurements. The temporal dynamics of algal blooms were primarily associated with nutrient (total dissolved nitrogen and phosphorus) concentration in Taihu Lake from 1993 to 2015 (Zhang et al. 2018). Moreover, the nitrogen and phosphorus concentration in lakes were monitored as discrete points to demonstrate the roles of nutrient loads in eutrophication changes of several lakes (Dai et al. 2016; Liang et al. 2020; Tong et al. 2017; Yindong et al. 2021). Unfortunately, these previous findings only focused on individual and several hyper-eutrophic lakes for short periods, which made it difficult to provide comprehensive understanding of factors in regulating regional patterns of lake eutrophication. Furthermore, plants actively participate in terrestrial water and nutrient cycling, and these abovementioned studies

cannot consider the dynamic roles of terrestrial ecosystems in influencing runoff and leached nutrients from land to lakes.

To fill these two knowledge gaps mentioned above, we employed a process-based dynamic vegetation model, LPJ-GUESS together with statistical analysis to reveal how terrestrial ecosystem processes are linked to regional patterns of eutrophication. More specifically, we aim to: 1) quantify temporal and spatial patterns of terrestrial nutrient exports to fifty large lakes in the Yangtze Plain for the past forty years; 2) determine linkages between the changes in nutrient and environment variables, and satellite-observed eutrophication changes; and 3) analyze the overall driving factors for regional eutrophication for the period from 2003 to 2011 in the Yangtze Plain.

2. Materials and Methods

2.1 Study area

The Yangtze Plain (Fig. 1), located in the middle and lower basin of Yangtze River, covers a total area of ~7850000 km² from Hunan Province to Shanghai City and has been experiencing rapid urbanization and economic growth (Feng et al. 2019; Hou et al. 2017). The region is characterized by the sub-tropical monsoon climate, with annual precipitation over 1000 mm/yr and average temperatures around 15°C. The abundant precipitation provides the main water source for ~5900 lakes and reservoirs (Guan et al. 2020; Guan et al. 2018). Yangtze Plain functions as one of top three grain-production bases (mainly grain and oil) in China. The total agricultural area is about 100 million hectares and produce approximately 54% of national grain yields (Chen et al. 2020). Such a huge agricultural system demands substantial chemical fertilizer to enhance grain yield to accommodate the rapid population growth (Zuo et al. 2018). Previous study has reported that there is generally low nitrogen use efficiency for crops, causing excessive nutrients leaching into local surface water (Zhang et al. 2015). Furthermore, rapid urbanization and economic growth has shrank arable lands, mainly on the eastern parts of Yangtze Plain, since the Reform and Opening-up of China (Chen et al. 2019; Zuo et al. 2018). The industrial and urban discharged wastewater should also be traced and analyzed in terms of their impacts on water environments in lakes of Yangtze Plain.

Figure 1. Locations of fifty large lakes in the Yangtze Plain, China. **a).** The numbers show the ID number of each studied lake, and names of each lake are listed in Table S2. **b).** The zoomed-in area of Wuhan region (red box) and the surrounding lakes. **c).** Locations of Yangtze River and Yangtze Plain in China.

2.2 Dynamic vegetation model

LPJ-GUESS, a dynamic vegetation model (Smith et al. 2001; Smith et al. 2014), was employed here to simulate vegetation dynamics, soil biogeochemistry, carbon and nitrogen cycling on Yangtze Plain. LPJ-GUESS is driven by daily climate data (i.e., temperature, precipitation and short-wave radiation), and has been widely used to simulate ecosystem carbon and nitrogen fluxes at regional to global scales (Smith et al. 2014). The model includes both natural plant functional types (PFTs) and crop function types (CFTs) to represent different types of plants and crops (Olin et al. 2015). Both PFTs and CFTs are characterized by different bio-climatic and physiological parameters, such as minimum/maximum growing temperatures, photosynthetic pathway, growth form, phenology, allometry, rates of establishment and mortality (Sitch et al. 2003; Smith et al. 2014), which determine their competitiveness for resources like light, water and nutrients and their productivity. The annual fractions of land use types and CFT distribution for each grid cell are read from input datasets. Crop management, including irrigation, fertilization and rotation schemes, are also applied for each CFT to represent agricultural practices (Olin et al. 2015).

In LPJ-GUESS, daily fluxes of carbon and nitrogen between ecosystems and the atmosphere are simulated, and for PFTs, daily net primary production (NPP) is accumulated through a year and allocated to different plant organs (leaves, fine roots, and stem) at the end of each year. The carbon allocation for crops (CFTs) occurs on a daily step

and is influenced by daily NPP and crop development stages (Olin et al. 2015). Dead leaf, wood and root enter soil litter C and N pools. In the model, there are in total 11 soil carbon pools with different decomposition rates (Parton et al. 1993; Parton et al. 2010). The C and N transfers among the C pools are influenced by soil temperature, water content and C-N ratios of receiving pools (Smith et al. 2014). Vegetation takes up mineral N via roots for growth and development. Apart from plant uptake, soil N is influenced by atmospheric deposition, plant biological fixation, nutrient gaseous losses and decomposition of SOM, and can be leached with runoff in the forms of dissolved organic (DON) and inorganic (DIN) nitrogen. DON is computed daily as a fraction of the decomposition rate of the soil microbial SOM pool and is affected by percolation, while DIN is based on daily percolation and available mineral N.

Crops are initialized with C mass from seeds, they also have an initial N content based on the CFT's C:N_{min} value. Fertilizer and manure were applied three times during the growing period and the application rates at each time were defined for each crop as fractions of the total application amount (Lindeskog et al. 2013). Daily carbon allocation varies with crop development status, defined as development stages in LPJ-GUESS, where details about carbon allocation at different development stages can be found in (Olin et al. 2015).

In this study, we used 11 CFTs to represent the majority of crops in Yangtze Plain. Hybrid and super-hybrid rice are widely distributed in this region, characterized by high grain yield in a short growing season. The high grain yield is associated with enhanced photosynthesis rates due to higher chlorophyll and Rubisco contents in leaves than normal rice (Yuan et al. 1998). Therefore, we calibrated the relationship between leaf N content and the maximum catalytic capacity of Rubisco (V_{max}) in LPJ-GUESS via optimization of grain yield (Haxeltine and Prentice 1996).

$$N = pV_m^{25} + N_0 \quad (1)$$

where N represents the foliage N content, V_m^{25} is the maximum catalytic capacity of Rubisco at 25°C. p and N_0 are empirical parameters. The parameter, p , is largely reduced to increase the rubisco capacity for super-hybrid rice (Table A1). Furthermore, super-hybrid rice has higher a specific leaf area (SLA, in Table A1), compared with normal rice (Huang et al. 2016), which could benefit crop productivity via potentially more intercepted light through the canopy.

LPJ-GUESS runs on three land cover types (i.e., cropland, natural land and grassland) with a 500-year spin-up to perform land processes on Yangtze Plain from 1979 to 2018. Due to limited data before 1992 and after 2015, crop distributions, land cover fraction and terrestrial N application were kept constant at the 1992 level for the period 1979

-1992 and at the 2015 level for the period after 2015.

2.3 Study datasets.

2.3.1 LPJ-GUESS input datasets

LPJ-GUESS input datasets include gridded climate, land cover fraction, chemical fertilizer and manure, gridded crop cultivation and soil properties. The climate data, daily air temperature, precipitation and shortwave radiation, were obtained from China Meteorological Forcing Dataset (CMFD) (He et al. 2020b), with a spatial resolution of 0.1° and coverage from 1979 to 2018. The Climate Change Initiative Land Cover (CCI-LC version 2.0) dataset was used to derive annual land cover fractions of urban, cropland, pasture and natural area from 1992 to 2015 by regrouping the original 37 land cover classes with a spatial resolution of 300m into these four fractions at a spatial resolution of 0.1° (Defourny et al. 2012) (for details see Section S1). Soil properties, consisting of sand, clay and silt fractions, organic carbon content, C:N ratio, pH and bulk density, were extracted from the World Inventory of Soil property Estimates (WISE30sec) with a spatial resolution of $30''$ (Batjes 2016), which were resampled to a spatial resolution of 0.1° based on the soil properties of the dominant FAO soil unit within a 0.1° grid cell. The chemical fertilizer usage and manure N data were both derived from global chemical fertilizer usage data from 1961 to 2013 published by (Lu and Tian 2017) and global manure datasets from 1860 to 2014 generated by (Zhang et al. 2017), with spatial resolutions of 0.5° and $0.5'$, respectively. The chemical fertilizer usage and manure N data were resampled to a spatial resolution of 0.1° via the nearest neighbor method embedded in Python GDAL (version 2.4.1).

Crop cultivation datasets, including crop type distribution, sowing and harvesting dates of crops, were interpolated from field station-based datasets from 1992 to 2015 (total of 92 observation stations across the Yangtze Plain), which were obtained from the China Meteorological Data Service Center. There were in total 11 main crops grown in the Yangtze Plain (Table S1), where three crop types were found as crop rotations, with combinations of two crops cultivated in one year: 1) early-season rice and late-season rice; 2) winter wheat and summer maize; 3) winter wheat and soybean. The details of the interpolation of these station-based data are described in section S3.

2.3.2 Evaluation of LPJ-GUESS

Three types of datasets were used to evaluate the performance of LPJ-GUESS simulation: 1) GOSIF GPP product; 2) GIMMS LAI3g product, and 3) field-observed grain yield. The annual global GOSIF GPP products from 1992 to 2018 were produced by (40), which has a spatial resolution of 0.05° (Li and Xiao 2019). The annual GIMMS LAI3g

products cover the period of 1982 to 2011, with a spatial resolution of 0.25° (Zhu et al. 2013). The observed annual grain yield for ten main crops was obtained from 89 stations across the Yangtze Plain from 2000 to 2018 (Liu et al. 2010). Due to limited yield data for each crop, the average grain yield for each crop type was calculated to represent regional mean grain yield for comparison with simulated grain yield in Yangtze Plain.

2.3.3 Eutrophication data

Satellite-derived PEO published in Guan et al. (2020) is defined as the occurrence frequency of high chlorophyll-a concentration ($> 10 \text{ mg m}^{-3}$) or algal blooms for each study year. In details, for each lake pixel, the number of images with high chlorophyll-a concentration or algal blooms was divided with total valid MERIS observations of each year to get the annual PEO value. For the fifty study lakes in Yangtze Plain, the PEO values of lake pixels within each lake were averaged to get lake averaged PEO value to represent eutrophication status and changes in fifty large studied lakes in Yangtze Plain from 2003 to 2011. The PEO dataset has been used in the statistical analysis together with nutrient and environmental variables.

2.3.4 Other auxiliary datasets

The considered terrestrial P sources come from chemical fertilizer and manure, which were determined from global phosphorus fertilizer products and biological excrement (Lu and Tian 2017; Zhang et al. 2017). Manure phosphorus sources were estimated from manure nitrogen contents with N:P ratios of animal manure (Table A3). The N:P ratio was calculated from the total terrestrial nitrogen and phosphorus sources from 2003 to 2011. Industrial wastewater discharge for each lake catchment was collected and published in (Feng et al. 2019; Guan et al. 2020) to represent the influence of anthropogenic nutrient exports from urban systems.

2.4 Statistical analysis

We applied statistical analyses for determining possible drivers of the satellite-observed PEO changes. Seven explanatory variables (listed in Table S4) were used in a principal component analysis (PCA), including terrestrial nutrient exports and environmental factors. PCA was employed to assess how different variables are related from 2003 to 2011. For the PCA analysis, Z-score normalization was used (across all years and lakes) to remove the

influence of different magnitudes between explanatory variables. The first two principal components (PCs) were subsequently used to separate the studied lakes into five different classes using K-mean clustering (Krishna and Murty 1999), where the dominant class of each lake for the studied period was used for the classification. Finally, partial least-squared regression (PLSR) was used to assess the drivers of PEO in the five identified classes, where data samples in all studied lakes were also normalized by Z-scores in SIMCA 17 (Umetrics, version 13.0.3.0, Umeå, Sweden). Explanatory variables with a VIP (Variable Influence on Projection) < 0.5 were removed, and variance of the cross-validated residuals was considered for testing whether the PLSR model was statistically significant for each lake class.

3. Results and Discussion

3.1 Model evaluation

To evaluate the performance of LPJ-GUESS model, the simulated annual crop yield, leaf area index (LAI) and gross primary production (GPP) were compared with observation-based estimates. The crop yields for ten main crop types, averaged for the Yangtze Plain area, agreed well with observed values, with both mean relative errors (MRE) and root mean squared errors (RMSE) between simulated and observed grain yields lower than 10% (Fig. 2). Similar spatial patterns appeared between the simulated and satellite-derived LAI and GPP estimates (Fig. S2). The magnitudes of simulated LAI were in good agreement with GIMMS LAI3g estimates (Fig. S1a), while LPJ-GUESS overall underestimated GPP compared with GOSIF GPP (underestimation on average ~20%, Fig. S1b). Estimations of LAI for all grid cells showed a satisfactory accuracy with a MRE of ~15% and RMSE of 27%. Simulated LAI distributed mainly along the 1:1 line with GIMMS LAI3g, and overestimations were most pronounced in areas with large cropland fractions. Nevertheless, the overall accuracy of simulated GPP is considered acceptable for such a regional simulation with relatively low MRE and RMSE (~23%).

Figure 2. Comparison between the simulated and observed grain yield for ten main crops, averaged for crop productivity in Yangtze Plain from 2000 to 2015. Error bars show ± 1 standard deviation of all available grain yields. Observed grain yield for peanut and spring wheat are literature values (He et al. 2020a; Yao 2004).

3.1 Growing anthropogenic nutrient application in Yangtze Plain

The total N and P applications from chemical fertilizer and manure have clearly increased over the past forty years (Fig. 3), with average rates of $2.75 \text{ kg N ha}^{-1} \text{ yr}^{-2}$ and $0.51 \text{ kg P ha}^{-1} \text{ yr}^{-2}$, respectively, resulting in a three-fold increase over the study period. However, due to differences in the paces of the two elements, the N:P ratio shows a decreasing trend combined with strong fluctuation in the period until 2000 and a slight rise or stabilization for the last 15 years (Fig. 3), potentially reshaping soil and water nutrient over-enrichment in Yangtze Plain.

Figure 3. The annual inputs of anthropogenic nitrogen (N) and phosphorus (P) from chemical fertilizers and manure and their corresponding N:P ratio from 1979 to 2014. Data were averaged across the whole Yangtze Plain.

3.2 Temporal and spatial variability of leached nitrogen

We used LPJ-GUESS to simulate and quantify the impact of this enhanced application of fertilizer and manure on the nutrient surplus leached as potential nutrient sources for lake water eutrophication. In the Yangtze Plain, the simulated leached N from agricultural and natural land has increased significantly during the study period, with a considerably lower rate for natural ($\sim 0.2 \text{ kg N ha}^{-1} \text{ yr}^{-2}$, Fig. 4b) than for agricultural ecosystems ($\sim 4.5 \text{ kg N ha}^{-1} \text{ yr}^{-2}$, Fig. 4a), due to external inputs from fertilizer and manure to the latter. Considerable spatial differences in N leaching from cropland (CLN) and natural land (NLN) existed. Higher N leaching was simulated for the cropland area in the catchment of Dongting Lake (longitude range 110°E to 114°E), which was linked to higher fertilizer rates. A decrease of N leaching was simulated in the eastern parts of Yangtze Plain (Fig. 4c). NLN distributed differently between the south and north sides of Yangtze Plain (Fig. 4d), mainly because of differences in N sources from atmospheric deposition and biological fixation under different climatic conditions (Zhan et al. 2017).

Individually, all studied lake catchments were characterized by significantly increasing trends for CLN, but with different start points for the CLN increases (Fig. 4e): The CLN values for lake catchments in the western region (L01-L06) started to increase already around 1990, much earlier than the catchments for eastern lakes (L45-L50, starting approximately 2005), suggesting that the nutrient status in western lakes to be potentially affected earlier than in eastern lakes. Similarly, NLN for all studied lake catchments, except for Donghu Lake (L18), has significantly increased with generally lower rates than CLN values over the past forty years (Fig. 4f). Seven lake catchments dominated by natural vegetation exhibited higher NLN (i.e., L28, L30, L32, L35, L37, L38, L43) than the surrounding lakes, collectively distributed in the middle regions of Yangtze Plain (near Poyang Lake).

Figure 4. Temporal and spatial patterns of leached N from cropland (CLN) and natural area (NLN). **a)** and **b)**: Temporal changes of CLN and NLN, where solid red lines are linear trends between years and leached N. Rates are expressed per area cropland and natural land, respectively. **c)** and **d)**: Spatial patterns of CLN and NLN expressed per total catchment area (mean for 1979-2018), respectively. **e)** and **f)**: Inter-annual changes of mean CLN and NLN values averaged over lake catchment area from 1979-2018, with statistically significantly increased trends (Mann Kendall trend test, $p < 0.05$) annotated with ‘*’. The ID numbers of lakes are listed in Table S2.

3.3 Linking nutrient and environmental drivers with PEO changes

To understand the potential impacts of environmental factors and terrestrial nutrient inputs on lake eutrophication status, the modelled CLN, NLN, the observation-based anthropogenic P exports (AP), N-P ratio (NP) and industrial wastewater discharge (IW), together with potential environmental drivers temperature (T) and total runoff (TR), were investigated as potential drivers of lake eutrophication. Annual mean values of these drivers for 2003-2011 were

combined with satellite-observed PEO over fifty lakes of Yangtze Plain from. We first used principal component analysis (PCA) to group the 50 lakes into different classes based on the abovementioned seven driving factors, and then we employed partial least-squared regression (PLSR) models on these classes to quantify the potential contribution of nutrient and environmental factors to the changes of PEO. The PCA results showed that the first two principal components (PCs) explained 35.7% and 24.6% of variations in environmental and nutrient exports between lakes and years (Fig. 5a), where the first PC primarily consists of positive correlations with agriculture-related nutrients (i.e., CLN, NP and AP) and negative correlations with TR, NLN and IW, and the second PC reveals a positive dependence on TR, T, NLN and AP, but negative dependence on IW. Based on these two PCs, we grouped fifty lakes into five classes with similar nutrient and environmental drivers using a K-means method (Krishna and Murty 1999) (see Method sections for details). Although all five classes were characterized with high mean PEO (> 80%, Fig. 5b) and considerable variability around the means, different magnitudes of trends in the study period were found between classes. PEO values for the majority of the lakes in class II decreased with time, while the other classes were dominated by increasing trends of PEO, with the strongest increases occurring in class III (Fig. 5c). Lakes of Class II are mainly located at the eastern parts of Yangtze Plain, where lake catchments undergo rapid industrialization. Lakes and their associated catchments of Class III cover a large area of Yangtze Plain (50.6%) and include the two largest lakes of this region (i.e., Poyang Lake, L35 and Dongting Lake, L07 in Fig. 1). The PEO changes in this class are positively linked to NLN and TR, showing the large influences from natural area and land runoff. Totally, 12 lakes were clustered into Class I, aligning closely with AP, CLN and T, and 14 lakes, mainly distributed in the middle reach of Yangtze Plain, were clustered into Class IV, with some impacts from AP. Lakes of Class V with large fractions of cropland aligned with CLN and NP, and most of these lakes were located in the agriculture-dominated western parts of Yangtze Plain, especially in Hunan Province (Fig. 1).

287

288

289 **Figure 5.** Principal component analysis classifying lake eutrophication with the same drivers. **a).** Loading plots of

principal component analysis (PCA) based on seven explanatory variables. The color and size of scattering points represent the distribution of lakes on longitudinal orders and cropland fraction within lake catchments, respectively. The directions of explanatory variables were annotated with orange lines. **b)** and **c)** mean values and temporal trends of PEO from 2003 to 2011 in five derived classes, where colored circles represent mean values and temporal trend of each individual studied lake, with statistically significant trends represented as filled circles and non-significant trends as hollow circles based on Mann-Kendall trend analysis with the threshold value of p as 0.05 in **c)**. Red and black solid lines are mean and median values, respectively. The bottom and top of the boxes represent first and third quartile, and error bars are the 95% confidence intervals. CLN: cropland leached nitrogen; NLN: nature leached nitrogen; AP: anthropogenic phosphorus; NP: nitrogen-phosphorus ratio; IW: industrial wastewater; T: temperature; TR: total runoff.

Significant PLSR models between annual values of PEO and drivers for all lakes within each class were found for all five classes ($p < 0.05$, Fig 6), and for each class, different drivers were responsible for the PEO changes. Across all lakes (Fig. 6f), we found PEO variations to be positively linked to agricultural nutrients NP and CLN, but negatively linked to NLN, highlighting that agricultural activities could be responsible to the overall changes of lake PEO in Yangtze Plain. At the class level, Class II showed clear positive linkage of PEO with IW and T, but negative linkage to the agricultural related indices (i.e., CLN, NP & AP) and total runoff, and the PEO changes for all other classes appear to be positively linked to the agricultural activities. In Class II, the lakes are dominated by negative trends of PEO (Fig. 5c), and the PLSR model provides many possible drivers for this (Fig. 6b). The decreasing trends in IW (Fig. S5) are expected to be the mechanistic driver of PEO dynamics, while for the other four variables with significantly negative coefficients and positive trends in each variable (Fig. S5), the PLSR model provides correlations between these explanatory variables and PEO in Class II lakes that are mechanistically unlikely (Fig. 5c). Furthermore, the large magnitude of IW changes observed in Class II lakes might suggest that the decreasing trends of PEO were mainly explained by the decreased exports of IW for the study period (Fig. S5), and that increased export of nutrients from cropland, although correlated, counterbalances this effect. Green industrial growth and wastewater treatment plants seem to have efficiently limited nutrient exports to local water bodies (Lyu et al. 2016). Notably, the attribution of driving factors to PEO changes based on these five classes could also be influenced by the spatial variations among lakes within each class, as the lakes have been grouped based on the dominant environmental and nutrient variables (PCA results). Therefore, we further examined the temporal trends of the significant factors and PEO for each lake within the same class (Fig. S5) to see if there are large variations among lake individuals

320 within the same class. We found that lakes within the same class often showed similar trends in explanatory variables
 321 and PEO as indicated by the regression coefficients in the PLSR models. For instance, the positive coefficients
 322 between PEO and IW in Class II lakes (Fig. 6b) were also seen as negative trends for both PEO and IW when we
 323 look at individual lakes. These alignments of trends and correlations support that the environmental and nutrient
 324 variables are mainly linked to the inter-annual changes in PEO in these five classes (Fig. S5). For Class III, there are
 325 different trends of T and PEO, although they showed positive coefficients, which in this case, indicates potential
 326 impacts from spatial variability of lakes in this class.

328 **Figure 6.** Regression coefficients of PLSR model between PEO and seven explanatory variables. **a-e** are class I-V,
 329 and **f** is all fifty studied lakes. Statistically significant models (CV-ANOVA) are annotated as *** for $p < 0.001$ and
 330 * for $p < 0.05$. Error bars represent ± 2 standard deviations of PLSR regression coefficients. CLN: cropland leached
 331 nitrogen; NLN: nature leached nitrogen; AP: anthropogenic phosphorus; NP: nitrogen-phosphorus ratio; IW:
 332 industrial wastewater; T: temperature; TR: total runoff.

3.4 Contributions of anthropogenic activities to eutrophication

336 In this study, we have attempted to determine possible causes of PEO for studied lakes using statistical methods. The
 337 results from these methods alone are unavoidably influenced by the correlations between individual variables, and/or
 338 by similar long-term trends in several explanatory variables that do not differ greatly between studied lake catchments.
 339 In such cases, the used statistical methods may result in correlations that do not allow differentiating between possible
 340 underlying mechanisms.

341
342
343
344
345
346
347
348
349
350
351
352
353
354
355
356
357
358
359
360
361
362
363
364
365
366
367
368
369
370

Through our analysis, we found out that lake eutrophication in Yangtze Plain is mainly associated with anthropogenic stresses, consisting of agriculture and industrialization. Industrialization-affected eutrophic lakes collectively distribute in the eastern parts of Yangtze Plain, while agricultural activities have large impacts on middle and western lake catchments with large cropland distribution in the catchments, most of which are located upstream of Dongting Lake (L7 in Fig. 4). Some lakes in the middle parts are characterized by PEO changes induced via large variability of land cover fraction, including two river-connected lakes (i.e., Dongting and Poyang Lake) for which PEO dynamics were not only affected by drivers in the local catchment, but also by upstream land use changes (Dai et al. 2017; Li et al. 2014). Current fertilizer usage in this region seems to largely exceed the demands for crop growth resulting in substantial nutrient exports to water bodies stimulating algae and phytoplankton growth (Zhang et al. 2015). The average N use efficiency simulated by LPJ-GUESS was about 34% in this region, which is much lower than the targeted goal of 60% for sustainable developments in China (Zhang et al. 2015). By maintaining high yield levels for food requirements of growing population (Long et al. 2018; Zhang et al. 2015), increasing use efficiency of chemical fertilizer in the agricultural area should be the main focus in this region to improve water quality in lakes of Yangtze Plain (Wang et al. 2019a).

Industrialization and economic growth can also contribute to increase nutrient exports available for phytoplankton communities mainly through industrial wastewater discharges (Wang et al. 2019b). Jiangsu Province, located in the eastern part of Yangtze Plain, experienced industrialization and economic development with annual industrialization and economic growth rates of 0.98% and 7.98%, respectively (Shen et al. 2020; Wang et al. 2020b). Under this rapid development, the decreased IW found in this region is on one hand associated with the national strategies and policies about green growth of industries, which encouraged industrial reuse and invested to advance wastewater treatment technology and installation of municipal wastewater treatment plants (Li et al. 2013; Lyu et al. 2016). On the other hand, the industrial structure transformation from secondary to tertiary industries also contributed to improve eutrophication status by decreasing industrial sewage discharge (Huang et al. 2015).

3.5 Limitations and Uncertainties

Terrestrial N and P sources were considered as nutrient elements for phytoplankton growth and development (Yi et al. 2017; Zhou et al. 2018). Unfortunately, most of the existing large-scale vegetation/ecosystem models lack of P-related processes in soil and vegetation (Che et al. 2014; Kerr and Wigneron 2020). We expect that leached P depends

on not only P fertilizer use, but also plant uptakes and soil supplies, similar to N processes (Fig. S6), which suggests that a further consideration of ecosystem processes on leached P and PEO will be needed. The P manure data, generated from N manure data via N-P ratios in animal excrements, are not fully independent from N manure inputs but are still important to include here as the nutrient sources in order to assess the contributions of P exports (i.e., chemical fertilizer and manure) from agricultural systems to surface water eutrophication (Li et al. 2017). Terrestrial nutrient sources are transported with runoff into local lakes, where part of these become accessible for phytoplankton. The lateral runoff and transport processes of terrestrial nutrients are influenced by soil properties, topography, and hydrological conditions (Solomon et al. 2015; Tang et al. 2015; Tang et al. 2014; Tang et al. 2018) which need to be further accounted for in order to assess the amount and dynamics of terrestrial nutrients into local lakes (Solomon et al. 2015). Apart from terrestrial nutrient sources, intensive aquaculture distributing across Yangtze Plain can be a potential nutrient source for water eutrophication (Luo et al. 2018; Wang et al. 2020a). Seventeen out of 50 Yangtze lakes have established enclosure fishery nets to increase fish production (Dai et al. 2019), where substantial amounts of fish baits were directly cast into aquaculture area for feeding fish. The surplus nutrients enable to contribute to more severe eutrophication (Guo and Li 2003). These limitations will need to be further explored to obtain a complete picture of nutrient sources available for phytoplankton communities and to reduce anthropogenic impacts on lake water quality and eutrophication.

4. Conclusion

In this study, we combined a dynamic vegetation model LPJ-GUESS with statistical analysis to reveal factors controlling eutrophication status in fifty large Yangtze lakes. During the past forty years, the agriculture-related nutrient exports (N&P) have significantly increased for all studied lakes, mainly linked to the enhanced chemical fertilizer usage. The leached nitrogen from natural land are much smaller than cropland. The averaged nitrogen leaching from cropland in the catchment of Dongting Lake is apparently greater than the middle- and eastern- parts of Yangtze Plain, while the leached nitrogen from natural land revealed considerable spatial variations from the north to south sides of Yangtze Plain linked to different climatic conditions. The overall PEO trends in the studied lakes were largely explained by the discharged industrial wastewater and leached nutrients from agricultural systems. There are spatial variations in terms of controlling factor responsible to the observed trends, for instance, nine lakes on the eastern Yangtze Plain were influenced by industrial wastewater, while most of lakes in the western Yangtze Plain, especially in Hunan Province, were relevant to agriculture activities. This study highlighted the roles of anthropogenic activities in water quality degradation and water pollution. Additionally, the approach of combining process-based

ecosystem model with satellite data to understand eutrophication changes could be applied on other regions and/or at larger scales, such as national and global scale, to provide critical information for policy-making to improve water environments.

Acknowledgments

This work was supported by the National Natural Science Foundation of China (NOs: 41971304). Qi Guan was funded by the SUSTech-UCPH Joint Program. Jing Tang was financially supported by Swedish FORMAS mobility grant (2016-01580). Stefan Olin acknowledges support from Lund University strong research areas MERGE and eSSENCE. We would like to appreciate European Space Agency (ESA) for publishing land cover dataset, China Meteorological Data Service Center for providing crop distribution and yield data.

Reference

- Batjes, N.H. (2016). Harmonized soil property values for broad-scale modelling (WISE30sec) with estimates of global soil carbon stocks. *J Geoderma*, 269, 61-68
- Beman, J.M., Arrigo, K.R., & Matson, P.A.J.N. (2005). Agricultural runoff fuels large phytoplankton blooms in vulnerable areas of the ocean, 434, 211-214
- Che, M.-L., Chen, B.-Z., Wang, Y., & Guo, X.-Y. (2014). Review of dynamic global vegetation models (DGVMs). *Ying yong sheng tai xue bao= The journal of applied ecology*, 25, 263-271
- Chen, C., Park, T., Wang, X., Piao, S., Xu, B., Chaturvedi, R.K., Fuchs, R., Brovkin, V., Ciais, P., Fensholt, R., Tømmervik, H., Bala, G., Zhu, Z., Nemani, R.R., & Myneni, R.B. (2019). China and India lead in greening of the world through land-use management. *Nature Sustainability*, 2, 122-129
- Chen, X., Wang, L., Niu, Z., Zhang, M., Li, C.a., & Li, J. (2020). The effects of projected climate change and extreme climate on maize and rice in the Yangtze River Basin, China. *Agricultural and Forest Meteorology*, 282-283
- Dai, M., Wang, J., Zhang, M., & Chen, X.J.I.J.o.S.R. (2017). Impact of the Three Gorges Project operation on the water exchange between Dongting Lake and the Yangtze River, 32, 506-514
- Dai, X., Qian, P., Ye, L., & Song, T. (2016). Changes in nitrogen and phosphorus concentrations in Lake Taihu, 1985-2015. *J Lake Sci*, 28, 935-943
- Dai, Y., Feng, L., Hou, X., Choi, C.Y., Liu, J., Cai, X., Shi, L., Zhang, Y., & Gibson, L. (2019). Policy-driven changes in enclosure fisheries of large lakes in the Yangtze Plain: Evidence from satellite imagery. *Sci Total Environ*, 688, 1286-1297
- Defourny, P., Kirches, G., Brockmann, C., Boettcher, M., Peters, M., Bontemps, S., Lamarche, C., Schlerf, M., & Santoro, M.J.P.U.G.V. (2012). Land cover CCI, 2
- Feng, L., Hou, X., & Zheng, Y. (2019). Monitoring and understanding the water transparency changes of fifty large lakes on the Yangtze Plain based on long-term MODIS observations. *Remote Sensing of Environment*, 221, 675-686
- Gooddy, D.C., Lapworth, D.J., Bennett, S.A., Heaton, T.H.E., Williams, P.J., & Surridge, B.W.J. (2016). A multi-stable isotope framework to understand eutrophication in aquatic ecosystems. *Water Res*, 88, 623-633
- Guan, Q., Feng, L., Hou, X., Schurgers, G., Zheng, Y., & Tang, J. (2020). Eutrophication changes in fifty large lakes on the Yangtze Plain of China derived from MERIS and OLCI observations. *Remote Sensing of Environment*, 246
- Guan, Q., Feng, L., & Kuang, X. (2018). Optical Classifications of Poyang Lake Water and Long-Term Dynamics Based on

439 MERIS Observations. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, 11, 4591-4603
 440 Guo, L. (2007). Ecology. Doing battle with the green monster of Taihu Lake. *Science*, 317, 1166
 441 Guo, L., & Li, Z. (2003). Effects of nitrogen and phosphorus from fish cage-culture on the communities of a shallow lake in
 442 middle Yangtze River basin of China. *J Aquaculture*, 226, 201-212
 443 Haxeltine, A., & Prentice, I.J.F.E. (1996). A general model for the light-use efficiency of primary production, 551-561
 444 He, D., Fang, S., Liang, H., Wang, E., & Wu, D.J.E.R.L. (2020a). Contrasting yield responses of winter and spring wheat to
 445 temperature rise in China, 15, 124038
 446 He, J., Yang, K., Tang, W., Lu, H., Qin, J., Chen, Y., & Li, X. (2020b). The first high-resolution meteorological forcing dataset
 447 for land process studies over China. *Sci Data*, 7, 25
 448 Hong, C., Burney, J.A., Pongratz, J., Nabel, J.E., Mueller, N.D., Jackson, R.B., & Davis, S.J.J.N. (2021). Global and regional
 449 drivers of land-use emissions in 1961–2017, 589, 554-561
 450 Hou, X., Feng, L., Duan, H., Chen, X., Sun, D., & Shi, K. (2017). Fifteen-year monitoring of the turbidity dynamics in large
 451 lakes and reservoirs in the middle and lower basin of the Yangtze River, China. *Remote Sensing of Environment*, 190, 107-
 452 121
 453 Huang, C., Zhang, M., Zou, J., Zhu, A.-x., Chen, X., Mi, Y., Wang, Y., Yang, H., & Li, Y. (2015). Changes in land use, climate
 454 and the environment during a period of rapid economic development in Jiangsu Province, China. *Science of The Total
 455 Environment*, 536, 173-181
 456 Huang, C., Zhang, Y., Huang, T., Yang, H., Li, Y., Zhang, Z., He, M., Hu, Z., Song, T., & Zhu, A.X. (2019). Long-term variation
 457 of phytoplankton biomass and physiology in Taihu lake as observed via MODIS satellite. *Water Res*, 153, 187-199
 458 Huang, J., Zhang, Y., Arhonditsis, G.B., Gao, J., Chen, Q., & Peng, J. (2020). The magnitude and drivers of harmful algal
 459 blooms in China's lakes and reservoirs: A national-scale characterization. *Water Res*, 181, 115902
 460 Huang, M., Shan, S., Zhou, X., Chen, J., Cao, F., Jiang, L., & Zou, Y. (2016). Leaf photosynthetic performance related to
 461 higher radiation use efficiency and grain yield in hybrid rice. *Field Crops Research*, 193, 87-93
 462 Kerr, Y.H., & Wigneron, J.-P. (2020). Vegetation models and observations A review. *Passive microwave remote sensing of
 463 land-atmosphere interactions* (pp. 317-344): De Gruyter
 464 Krishna, K., & Murty, M.N. (1999). Genetic K-means algorithm. *IEEE Transactions on Systems, Man, and Cybernetics, Part
 465 B (Cybernetics)*, 29, 433-439
 466 Lewis, W.M., Wurtsbaugh, W.A., & Paerl, H.W. (2011). Rationale for control of anthropogenic nitrogen and phosphorus to
 467 reduce eutrophication of inland waters. *Environ Sci Technol*, 45, 10300-10305
 468 Li, A.A., Stokal, M.M., Bai, Z.Z.H., Kroeze, C.C., Ma, L.L., & Zhang, F.F.S. (2017). Modelling reduced coastal eutrophication
 469 with increased crop yields in Chinese agriculture %J Soil Research, 55, 506-517
 470 Li, H.-M., Tang, H.-J., Shi, X.-Y., Zhang, C.-S., & Wang, X.-L.J.H.A. (2014). Increased nutrient loads from the Changjiang
 471 (Yangtze) River have led to increased harmful algal blooms, 39, 92-101
 472 Li, X., & Xiao, J. (2019). A Global, 0.05-Degree Product of Solar-Induced Chlorophyll Fluorescence Derived from OCO-2,
 473 MODIS, and Reanalysis Data. *Remote Sensing*, 11
 474 Li, Y., Luo, X., Huang, X., Wang, D., & Zhang, W. (2013). Life Cycle Assessment of a municipal wastewater treatment plant:
 475 a case study in Suzhou, China. *Journal of Cleaner Production*, 57, 221-227
 476 Liang, Z., Soranno, P.A., & Wagner, T. (2020). The role of phosphorus and nitrogen on chlorophyll a: Evidence from
 477 hundreds of lakes. *Water Research*, 185
 478 Lindeskog, M., Arneth, A., Bondeau, A., Waha, K., Seaquist, J., Olin, S., & Smith, B.J.E.S.D. (2013). Implications of
 479 accounting for land use in simulations of ecosystem carbon cycling in Africa, 4, 385-407
 480 Liu, S., Mo, X., Lin, Z., Xu, Y., Ji, J., Wen, G., & Richey, J. (2010). Crop yield responses to climate change in the Huang-Huai-
 481 Hai Plain of China. *Agricultural Water Management*, 97, 1195-1209
 482 Liu, X., Huang, Y., Xu, X., Li, X., Li, X., Ciais, P., Lin, P., Gong, K., Ziegler, A.D., & Chen, A.J.N.S. (2020). High-spatiotemporal-

483 resolution mapping of global urban change from 1985 to 2015, *3*, 564-570
 484 Long, S., Zhao, L., Shi, T., Li, J., Yang, J., Liu, H., Mao, G., Qiao, Z., & Yang, Y.J.J.o.C.P. (2018). Pollution control and cost
 485 analysis of wastewater treatment at industrial parks in Taihu and Haihe water basins, China, *172*, 2435-2442
 486 Lu, C., & Tian, H. (2017). Global nitrogen and phosphorus fertilizer use for agriculture production in the past half century:
 487 shifted hot spots and nutrient imbalance. *Earth System Science Data*, *9*, 181-192
 488 Luo, Z., Hu, S., & Chen, D. (2018). The trends of aquacultural nitrogen budget and its environmental implications in China.
 489 *Sci Rep*, *8*, 10877
 490 Lyu, S., Chen, W., Zhang, W., Fan, Y., & Jiao, W. (2016). Wastewater reclamation and reuse in China: opportunities and
 491 challenges. *Journal of Environmental Sciences*, *39*, 86-96
 492 Ma, R., Duan, H., Hu, C., Feng, X., Li, A., Ju, W., Jiang, J., & Yang, G. (2010). A half-century of changes in China's lakes:
 493 Global warming or human influence? *Geophysical Research Letters*, *37*
 494 Olin, S., Schurgers, G., Lindeskog, M., Wårlind, D., Smith, B., Bodin, P., Holmér, J., & Arneth, A. (2015). Modelling the
 495 response of yields and tissue C : N to changes in atmospheric CO₂ and N management in the main wheat regions of
 496 western Europe. *Biogeosciences*, *12*, 2489-2515
 497 Paerl, H.W., Xu, H., McCarthy, M.J., Zhu, G., Qin, B., Li, Y., & Gardner, W.S. (2011). Controlling harmful cyanobacterial
 498 blooms in a hyper-eutrophic lake (Lake Taihu, China): the need for a dual nutrient (N & P) management strategy. *Water*
 499 *Res*, *45*, 1973-1983
 500 Parton, W., Scurlock, J., Ojima, D., Gilmanov, T., Scholes, R., Schimel, D.S., Kirchner, T., Menaut, J.C., Seastedt, T., & Garcia
 501 Moya, E.J.G.b.c. (1993). Observations and modeling of biomass and soil organic matter dynamics for the grassland biome
 502 worldwide, *7*, 785-809
 503 Parton, W.J., Hanson, P.J., Swanston, C., Torn, M., Trumbore, S.E., Riley, W., & Kelly, R.J.J.o.G.R.B. (2010). ForCent model
 504 development and testing using the Enriched Background Isotope Study experiment, *115*
 505 Schindler, D.W., Hecky, R.E., Findlay, D., Stainton, M., Parker, B., Paterson, M., Beaty, K., Lyng, M., & Kasian, S.J.P.o.t.N.A.o.S.
 506 (2008). Eutrophication of lakes cannot be controlled by reducing nitrogen input: results of a 37-year whole-ecosystem
 507 experiment, *105*, 11254-11258
 508 Shen, F., Yang, L., He, X., Zhou, C., & Adams, J.M. (2020). Understanding the spatial-temporal variation of human footprint
 509 in Jiangsu Province, China, its anthropogenic and natural drivers and potential implications. *Scientific reports*, *10*, 1-12
 510 Shi, K., Zhang, Y., Xu, H., Zhu, G., Qin, B., Huang, C., Liu, X., Zhou, Y., & Lv, H. (2015). Long-Term Satellite Observations of
 511 Microcystin Concentrations in Lake Taihu during Cyanobacterial Bloom Periods. *Environ Sci Technol*, *49*, 6448-6456
 512 Sinha, E., Michalak, A.M., & Balaji, V. (2017). Eutrophication will increase during the 21st century as a result of
 513 precipitation changes, *357*, 405-408
 514 Sitch, S., Smith, B., Prentice, I.C., Arneth, A., Bondeau, A., Cramer, W., Kaplan, J.O., Levis, S., Lucht, W., & Sykes, M.T.J.G.c.b.
 515 (2003). Evaluation of ecosystem dynamics, plant geography and terrestrial carbon cycling in the LPJ dynamic global
 516 vegetation model, *9*, 161-185
 517 Smith, B., Prentice, I.C., Sykes, M.T.J.G.e., & biogeography (2001). Representation of vegetation dynamics in the modelling
 518 of terrestrial ecosystems: comparing two contrasting approaches within European climate space, 621-637
 519 Smith, B., Wårlind, D., Arneth, A., Hickler, T., Leadley, P., Siltberg, J., & Zaehle, S. (2014). Implications of incorporating N
 520 cycling and N limitations on primary production in an individual-based dynamic vegetation model. *Biogeosciences*, *11*,
 521 2027-2054
 522 Solomon, C.T., Jones, S.E., Weidel, B.C., Buffam, I., Fork, M.L., Karlsson, J., Larsen, S., Lennon, J.T., Read, J.S., Sadro, S., &
 523 Saros, J.E. (2015). Ecosystem Consequences of Changing Inputs of Terrestrial Dissolved Organic Matter to Lakes: Current
 524 Knowledge and Future Challenges. *Ecosystems*, *18*, 376-389
 525 Tang, J., Miller, P.A., Crill, P.M., Olin, S., & Pilesjo, P. (2015). Investigating the influence of two different flow routing
 526 algorithms on soil-water-vegetation interactions using the dynamic ecosystem model LPJ-GUESS. *Ecohydrology*, *8*, 570-

527 583

- 528 Tang, J., Pilesjö, P., Miller, P.A., Persson, A., Yang, Z., Hanna, E., & Callaghan, T.V.J.E. (2014). Incorporating topographic
529 indices into dynamic ecosystem modelling using LPJ - GUESS, 7, 1147-1162
- 530 Tang, J., Yurova, A.Y., Schurgers, G., Miller, P.A., Olin, S., Smith, B., Siewert, M.B., Olefeldt, D., Pilesjö, P., & Poska, A. (2018).
531 Drivers of dissolved organic carbon export in a subarctic catchment: Importance of microbial decomposition, sorption-
532 desorption, peatland and lateral flow. *Sci Total Environ*, 622-623, 260-274
- 533 Tong, Y., Zhang, W., Wang, X., Couture, R.-M., Larssen, T., Zhao, Y., Li, J., Liang, H., Liu, X., Bu, X., He, W., Zhang, Q., & Lin,
534 Y. (2017). Decline in Chinese lake phosphorus concentration accompanied by shift in sources since 2006. *Nature*
535 *Geoscience*, 10, 507-511
- 536 Wang, J., Beusen, A.H.W., Liu, X., & Bouwman, A.F. (2020a). Aquaculture Production is a Large, Spatially Concentrated
537 Source of Nutrients in Chinese Freshwater and Coastal Seas. *Environ Sci Technol*, 54, 1464-1474
- 538 Wang, J., Fu, P., Wang, F., Fahad, S., Mohapatra, P.K., Chen, Y., Zhang, C., Peng, S., Cui, K., Nie, L., & Huang, J. (2019a).
539 Optimizing nitrogen management to balance rice yield and environmental risk in the Yangtze River's middle reaches.
540 *Environ Sci Pollut Res Int*, 26, 4901-4912
- 541 Wang, M., Stokal, M., Burek, P., Kroeze, C., Ma, L., & Janssen, A.B.G. (2019b). Excess nutrient loads to Lake Taihu:
542 Opportunities for nutrient reduction. *Sci Total Environ*, 664, 865-873
- 543 Wang, Z., Zhao, L., & Wang, Y. (2020b). An empirical correlation mechanism of economic growth and marine pollution: A
544 case study of 11 coastal provinces and cities in China. *Ocean & Coastal Management*, 198, 105380
- 545 Wilhelm, S.W., Farnsley, S.E., LeCleir, G.R., Layton, A.C., Satchwell, M.F., DeBruyn, J.M., Boyer, G.L., Zhu, G., & Paerl, H.W.
546 (2011). The relationships between nutrients, cyanobacterial toxins and the microbial community in Taihu (Lake Tai), China.
547 *Harmful Algae*, 10, 207-215
- 548 Xu, H., Paerl, H.W., Qin, B., Zhu, G., Hall, N.S., & Wu, Y. (2015). Determining critical nutrient thresholds needed to control
549 harmful cyanobacterial blooms in eutrophic Lake Taihu, China. *Environ Sci Technol*, 49, 1051-1059
- 550 Yao, G.J.U.o.G. (2004). Peanut production and utilization in the People's Republic of China
- 551 Yi, Q., Chen, Q., Hu, L., & Shi, W. (2017). Tracking Nitrogen Sources, Transformation, and Transport at a Basin Scale with
552 Complex Plain River Networks. *Environ Sci Technol*, 51, 5396-5403
- 553 Yindong, T., Xiwen, X., Miao, Q., Jingjing, S., Yiyan, Z., Wei, Z., Mengzhu, W., Xuejun, W., & Yang, Z. (2021). Lake warming
554 intensifies the seasonal pattern of internal nutrient cycling in the eutrophic lake and potential impacts on algal blooms.
555 *Water Res*, 188, 116570
- 556 Yuan, L., Denning, G., & Mew, T.J.D.G., Mew TW, editors (1998). Hybrid rice breeding for super high yield, 10-12
- 557 Zhan, X., Bo, Y., Zhou, F., Liu, X., Paerl, H.W., Shen, J., Wang, R., Li, F., Tao, S., Dong, Y., & Tang, X. (2017). Evidence for the
558 Importance of Atmospheric Nitrogen Deposition to Eutrophic Lake Dianchi, China. *Environmental Science & Technology*,
559 51, 6699-6708
- 560 Zhang, B., Tian, H., Lu, C., Dangal, S.R.S., Yang, J., & Pan, S. (2017). Global manure nitrogen production and application in
561 cropland during 1860–2014: a 5 arcmin gridded global dataset for Earth system modeling. *Earth System Science Data*, 9,
562 667-678
- 563 Zhang, M., Shi, X., Yang, Z., Yu, Y., Shi, L., & Qin, B. (2018). Long-term dynamics and drivers of phytoplankton biomass in
564 eutrophic Lake Taihu. *Sci Total Environ*, 645, 876-886
- 565 Zhang, X., Davidson, E.A., Mauzerall, D.L., Searchinger, T.D., Dumas, P., & Shen, Y.J.N. (2015). Managing nitrogen for
566 sustainable development, 528, 51-59
- 567 Zhao, Z., Cao, Y., Fan, Y., Yang, H., Feng, X., Li, L., Zhang, H., Xing, L., & Zhao, M. (2019). Ladderane records over the last
568 century in the East China sea: Proxies for anammox and eutrophication changes. *Water Res*, 156, 297-304
- 569 Zhou, Y., Xiao, Q., Yao, X., Zhang, Y., Zhang, M., Shi, K., Lee, X., Podgorski, D.C., Qin, B., Spencer, R.G.M., & Jeppesen, E.
570 (2018). Accumulation of Terrestrial Dissolved Organic Matter Potentially Enhances Dissolved Methane Levels in Eutrophic

571 Lake Taihu, China. *Environ Sci Technol*, 52, 10297-10306

572 Zhu, Z., Bi, J., Pan, Y., Ganguly, S., Anav, A., Xu, L., Samanta, A., Piao, S., Nemani, R.R., & Myneni, R.B.J.R.s. (2013). Global
573 data sets of vegetation leaf area index (LAI) 3g and fraction of photosynthetically active radiation (FPAR) 3g derived from
574 global inventory modeling and mapping studies (GIMMS) normalized difference vegetation index (NDVI3g) for the period
575 1981 to 2011, 5, 927-948

576 Zou, W., Zhu, G., Cai, Y., Xu, H., Zhu, M., Gong, Z., Zhang, Y., & Qin, B. (2020). Quantifying the dependence of cyanobacterial
577 growth to nutrient for the eutrophication management of temperate-subtropical shallow lakes. *Water Research*, 177

578 Zuo, L., Zhang, Z., Carlson, K.M., MacDonald, G.K., Brauman, K.A., Liu, Y., Zhang, W., Zhang, H., Wu, W., Zhao, X., Wang, X.,
579 Liu, B., Yi, L., Wen, Q., Liu, F., Xu, J., Hu, S., Sun, F., Gerber, J.S., & West, P.C. (2018). Progress towards sustainable
580 intensification in China challenged by land-use change. *Nature Sustainability*, 1, 304-313

581

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- [SupplementaryMaterial.docx](#)