



Riverine phosphorus gain and loss across the conterminous United States

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Abstract. Excess riverine phosphorus represents a preeminent catalyst for water quality degradation. Spatial mapping and characterization of the net gain and loss of riverine phosphorus help discern the critical source areas. Here, we developed a dataset encompassing phosphate (PO_4^{3-}) and total phosphorus (TP) gain and loss across catchments in the conterminous United States (CONUS). We compiled 51,394 PO_4^{3-} and 285,675 TP concentration data points and estimated PO_4^{3-} and TP loads at 963 and 2,317 stations, respectively. Next, we leveraged the upstream-downstream topology information from the National Hydrography Dataset Plus (NHDPlus) catchment map at the Hydrologic Unit Catalogue-12 (HUC12) level to derive the net gain and loss of riverine phosphorus across catchments in the CONUS. Such maps can be used to estimate potential contributions of point and non-point sources to riverine phosphorus pollution at refined spatial scales, identify different major factors controlling local riverine P gain and loss compared to P loads, and evaluate watershed model's fidelity for representing riverine P cycling. The resultant dataset is provided in Excel (.xlsx) format, accessible at Figshare (<https://doi.org/10.6084/m9.figshare.28509317>, Wang et al., 2025). Leveraging the HUC12 information for spatialization, the new datasets aim to address the existing gap in regional characterization of riverine phosphorus and support effective management practices across the CONUS.



26 1 Introduction

27 Eutrophication is a widespread water quality challenge across the globe, with significant economic cost (e.g., \$1 billion in
 28 Europe and \$2.2 billion annually in the United States (U.S.)) (Wurtsbaugh et al., 2019). Excess phosphorus (P) is a primary
 29 contributor to eutrophication in streams and rivers, especially in intensive agricultural regions (Brownlie et al., 2022; Royer et
 30 al., 2006a). Riverine export of P is also a major contributor to oxygen-depleted dead zones in coastal waters, causing damage
 31 to underwater life (Diaz and Rosenberg, 2008). There is an urgent need for global actions to reduce P pollution for the
 32 environment and human health (UNEP, 2025).

33 Nonpoint or diffuse sources, particularly nutrients applied to agroecosystems, are often recognized as the primary source of
 34 water pollution (Carpenter et al., 1998). P surplus in agricultural soils due to excessive fertilization and manure application
 35 can be transported to water bodies through surface runoff and groundwater pathways, and cause persistent water pollution
 36 (Stackpoole et al., 2019). The diffuse nature of nonpoint source pollution poses challenges for directly identifying and
 37 regulating critical source areas. Existing riverine P pollution databases mainly focus on certain agricultural areas (Ringeval et
 38 al., 2024). Given the considerable spatial variation in P inputs to rivers (Arheimer and Lidén, 2000; Stackpoole et al., 2019;
 39 Zhang et al., 2017), there is a lack of large-scale riverine P datasets at sufficient spatial scales across the conterminous United
 40 States (CONUS) to quantify and analyze riverine P gain and loss. Such datasets, in conjunction with other observed and
 41 modelled P data (e.g., point source discharge) help identify regions with high non-point source P inputs, thereby supporting
 42 more effective targeting of measures for P pollution control. In addition, the datasets can also be used to assess fidelity of
 43 distributed watershed models and understand key factors influencing local riverine P cycling.

44 In this study, we aim to develop new datasets for spatial characterization of riverine P gain and loss across the CONUS, to
 45 help identify critical source areas and improve prioritization and implementation of nutrient management activities. The
 46 subsequent sections of this paper include the method used to generate spatial riverine P gain and loss (Section 2), results
 47 detailing the P dataset (Section 3), discussion of influencing factors and potential uncertainties (Section 4), codes and data
 48 availability (Section 5), and conclusions (Section 6).

50 2 Materials and Methods

51 2.1 Overview

52 To estimate riverine P gain and loss data across the CONUS, we compiled streamflow and P concentration data (i.e., unfiltered
 53 phosphate (PO_4^{3-})) and total phosphorus (TP) at over 1,000 hydrological stations in the CONUS and calculated P loads at those
 54 stations using the Load Estimator (LOADEST) program (Runkel et al., 2004) (Fig. 1). Next, we estimated P gain and loss
 55 across the catchments measured by one downstream station and its immediate upstream stations using the upstream-
 56 downstream connectivity information contained in the National Hydrography Dataset Plus (NHDPlus) catchments



(https://nhdplus.com/NHDPlus/NHDPlusV2_data.php), resulting in 547 and 1,225 unique Hydrologic Unit Catalogue (HUC) groups for PO_4^{3-} and TP, respectively. Each HUC group has a unique pair of downstream and upstream stations that allows us to calculate the gain and loss of riverine P (as illustrated in Fig. S1 in the Supplemental Information). Note that headwater HUC groups only have one downstream station without upstream stations draining to them. Due to differences in data availability, the riverine PO_4^{3-} and TP gain and loss data cover 52,020 and 65,735 Hydrologic Unit Catalogue-12 (HUC12) catchments, respectively. Then we estimated potential contribution to P pollution from nonpoint sources by subtracting upstream P inputs and point source P inputs from the riverine P gain and loss in each catchment. Finally, we used land cover and climate data to evaluate major controls of riverine P gain and loss.

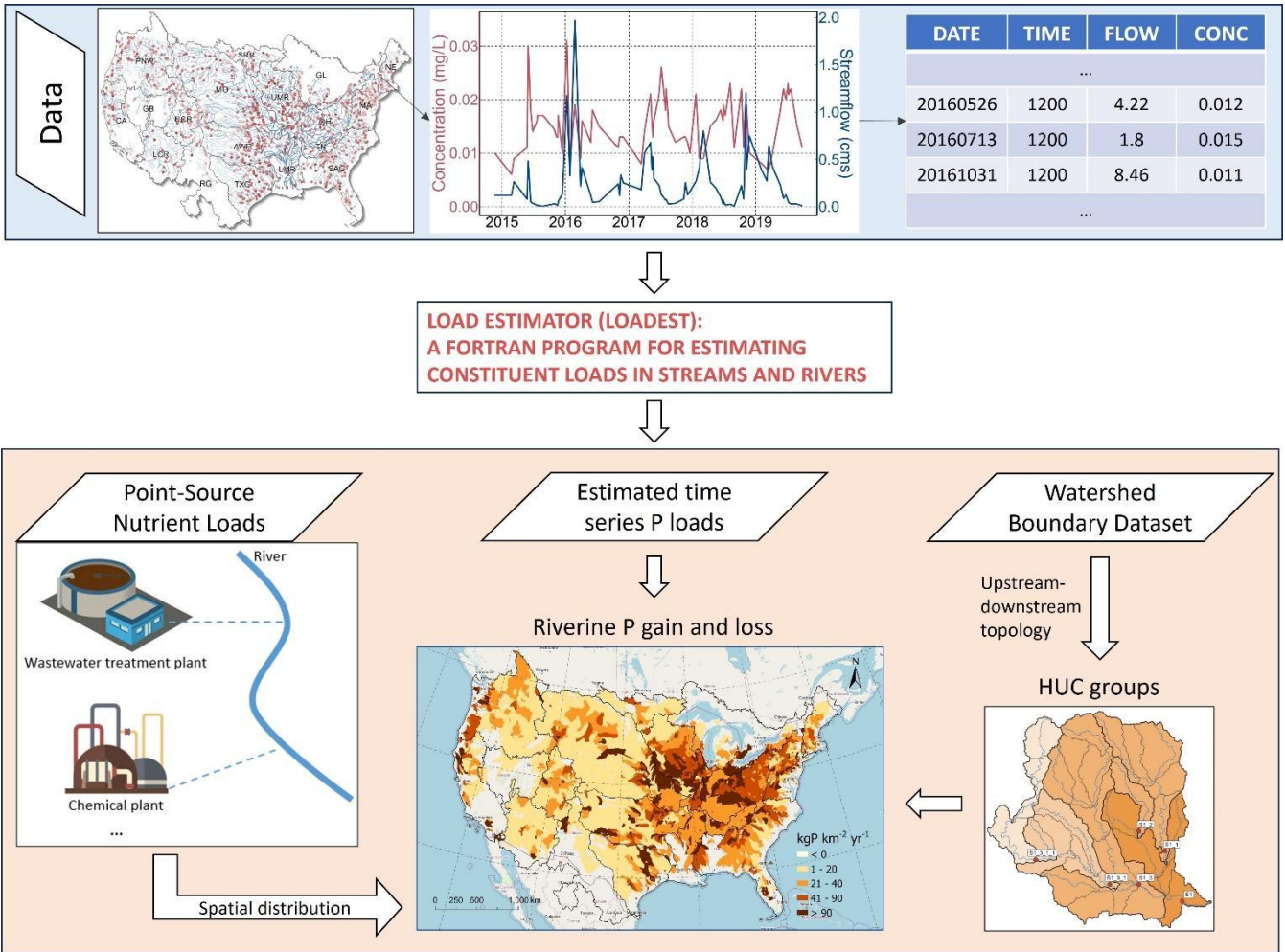


Figure 1: Overview of the generation of TP and PO_4^{3-} gain and loss data across the CONUS. A more detailed description and higher resolution figure about HUC group generation can be found in Text S2 and Fig. S1.



68 2.2 Study area

69 The CONUS (i.e., the lower 48 states of the U.S.) is located in North America from 98° 34' to 46° 20' W longitude and from
 70 39° 49' to 41° 43' N latitude, covering an area of 8,080,464.3 km² with a north-to-south distance of approximately 2,660 km.
 71 The terrain features higher elevations in the west and flatter areas in the east. Based on the Watershed Boundary Dataset (WBD;
 72 <https://water.usgs.gov/GIS/huc.html>), the CONUS includes 18 major watersheds, encompassing several large rivers such as
 73 the Mississippi and Colorado Rivers.

74 2.3 Data compilation

75 We compiled 51,394 PO₄³⁻ (USGS parameter code 00650) concentration data from 963 hydrological stations (spanning from
 76 1952 to 2022) and 285,675 TP (USGS parameter code 00665) observations from 2,317 hydrological stations (spanning from
 77 1958 to 2023) across the CONUS from the Water Quality Portal (Read et al., 2017). For each P observation, we identified co-
 78 located hydrological stations (Wang, Zhang, Zhao, et al., 2024) and downloaded and processed daily streamflow data from the
 79 U.S. Geological Survey (USGS) National Water Information System. We calculated an average P concentration where there
 80 were multiple P concentration observations on the same day. Before calculating the P load at a hydrological station with the
 81 LOADEST model, we excluded stations with less than 12 data points. Thus, we finally selected 547 stations for PO₄³⁻ and
 82 1,225 stations for TP. For TP, the "Point-Source Nutrient Loads to Streams of the Conterminous United States" dataset provides
 83 estimated point-source inputs at the HUC12 level (Skinner and Maupin, 2019). This allowed us to aggregate the total TP input
 84 to rivers for the catchments used to calculate riverine TP gain and loss. Note that the point source dataset does not contain
 85 PO₄³⁻.

86 Land cover and climatic controls of riverine P gain and loss were also assessed. Land cover data were derived from the National
 87 Land Cover Database (NLCD; <https://doi.org/10.5066/P94UXNTS>), which provided long-term average information on
 88 various land cover types: barren land, crops, forest, hay, herbs, impervious surfaces, scrub, water, herbaceous wetlands, and
 89 woody wetlands (Homer et al., 2012). Climate data were sourced from the PRISM dataset
 90 (<https://www.prism.oregonstate.edu/>), including annual average temperature and total precipitation (Page et al., 2021). Using
 91 upstream-downstream topology information, we calculated the total area of each land cover type from the headwater to the
 92 current catchment at the HUC12 scale, representing their cumulative impact. For climate data, the local climate within each
 93 HUC12 was used. The P surplus was accessed from the National Inventory of Phosphorus (NIP), which provides major inputs
 94 and outputs of reactive P at the HUC8 scale across the CONUS (Sabo et al., 2021).

95 2.4 Riverine P gain and loss across catchments in the CONUS

96 Riverine P gain and loss was estimated by calculating the difference between P loads at a downstream hydrological station and
 97 the sum of P loads from its neighbouring upstream stations. For multiple USGS stations located in the same HUC12 catchment,
 98 we kept only one station on the mainstem of the river that is closest to the outlet of the HUC12 catchment, by comparing the



drainage area of the gaging station and the HUC12 catchment in which it is located. For headwaters, since there are no upstream gages, the P load was used as the net riverine gain. The upstream-downstream topology relationship between the hydrological stations was derived from the HUC12 catchments from the watershed boundary dataset (WBD; <https://water.usgs.gov/GIS/huc.html>). Such a method has been outlined and tested by Qiu et al. (2023) (Text S2). As explained above, we identified 547 and 1,225 unique HUC groups for PO_4^{3-} and TP, respectively. Note that each HUC group includes multiple HUC12 polygons and these HUC12 catchments share the same gain and loss data.

For each HUC group, the balance of riverine P can be expressed as follows:

$$\begin{aligned} P \text{ load at downstream outlet} = & (P \text{ loads from upstream inputs}) + (P \text{ from point sources}) - \\ & (Riverine \text{ removal of } P \text{ from point sources}) + (P \text{ from non-point sources}) - \\ & (Riverine \text{ removal of } P \text{ from non-point sources}) \end{aligned} \quad (1)$$

Rearranging the above equation leads to:

$$\begin{aligned} (P \text{ from nonpoint sources}) = & P \text{ gain and loss} - (P \text{ from point sources}) + \\ & (Riverine \text{ removal of } P \text{ from point sources}) + (Riverine \text{ removal of } P \text{ from non-point sources}) \end{aligned} \quad (2)$$

where $P \text{ gain and loss} = (P \text{ load at downstream outlet}) - (P \text{ loads from upstream inputs})$.

Given that rivers often remove a small portion of P load (e.g., 12%) (Maavara et al., 2015), we assumed that $(P \text{ from nonpoint sources}) = P \text{ gain and loss} - (P \text{ from point sources})$ is a lower-end estimate of the nonpoint source contribution to riverine P for each HUC group. Since only TP from point sources is available, we derived nonpoint-source TP loads but not for PO_4^{3-} .

2.5 Evaluation of estimated riverine load

We evaluated the consistency of the PO_4^{3-} and TP loads against another independent dataset derived with the Weighted Regressions on Time, Discharge, and Season (WRTDS) model (Hirsch et al., 2010; Zhang and Hirsch, 2019). First, we compared multi-year average TP loads from 151 hydrological stations. We also evaluated the estimated unfiltered PO_4^{3-} loads, which assess the mass of reactive P susceptible to being released in the water column under various redox conditions. Furthermore, the reliability of the upstream-downstream connectivity information is important for deriving the drainage area of HUC groups that are controlled by pairs of upstream and downstream hydrological stations. Here we used a quality-checked and corrected NHDPlus HUC12 catchment map (Wang, Zhang, & Zhao, 2024) that has been verified for reliably deriving the drainage area of each USGS hydrologic station as compared to the USGS GAGES-II reported values (Falcone and Survey, 2011). These efforts helped ensure the quality of the riverine P gain and loss data developed in this study.

2.6 Analysis of environmental controls

Recent studies reveal that shifts in land use, agricultural practices, and climatic conditions have introduced a pervasive increase in soluble P concentrations across many different watersheds (Houser and Richardson, 2010; Singh et al., 2023). To assess the



spatial factors influencing riverine P gain and loss, we employed random forest modelling to evaluate the relative importance of multiple environmental variables (Breiman, 2001). These factors were categorized into three groups: climatic factors, land cover types, and additional influences such as cumulative agricultural inputs and upstream loads. Given that the NIP dataset is only available at the HUC8 scale and some HUC groups are larger than the HUC8 catchment areas, we calculated the cumulative agricultural inputs at the HUC4 scale. In more detail, we used the ranger package, optimizing the model structure with the caret package in R. Key tuning parameters included the number of variables to use in each split (mtry), the number of trees (n_trees) and the minimum size of data points before splitting a tree (min_n). The tuning process was performed by doing a grid search for mtry (2-6) and min_n (10-20), then a second search was performed to find the optimal n_trees parameter (500-3000). To minimize random effects, the model was run 10 times, and we calculated the average importance value and harmonic mean p-value (Wilson, 2019).

3 Results

3.1 Riverine phosphorus data

We created two datasets, "Riverine PO₄³⁻" and "Riverine TP," that encapsulate estimated multi-year average riverine gain and loss and loads, as well as point source and nonpoint source contributions for each HUC group for PO₄³⁻ and TP, respectively (Table 1). Complementing this information, the datasets encompass the location (i.e., longitude and latitude) of the outlet of the HUC group, the area of the HUC group, the count of observations used to calculate P loads, and commencement and termination years of observed data, to facilitate user-defined subsetting of the datasets. Additional information regarding the regression model is also included, such as the form of the regression model selected by LOADEST and the associated coefficient of determination (r^2) values.

Across the board, the average r^2 values for the best-fit model (Table S1) across all sites are 0.76 for PO₄³⁻ loads and 0.83 for TP loads. It is noteworthy, however, that certain hydrologic stations exhibited low r^2 values due to the limited availability of paired P concentration with streamflow data for regression.

Table 1. Data records in the "Riverine PO₄³⁻" and "Riverine TP" datasets.

Field name	Description
Station ID	U.S. Geological Survey designated ID; Note that this ID is also used to denote a unique HUC group
Lat	Latitude of the hydrologic station at the outlet of a HUC group
Long	Longitude of the hydrologic station at the outlet of a HUC group
Area	Area of the HUC group
Load	The amount of PO ₄ ³⁻ or TP loads at the outlet hydrologic station of a HUC group (kgP yr ⁻¹)



P gain and loss	The difference between P loads at the outlet of a HUC group and all its immediate upstream stations (kgP km ⁻² yr ⁻¹)
NonPts TP contribution*	Nonpoint-source contribution to riverine phosphorus from a HUC group (kgP km ⁻² yr ⁻¹)
Pts TP load	Point-source TP loads (kg yr ⁻¹) from a HUC group
obsNum	The number of phosphorus concentration data with paired streamflow data
startYr	The starting year of the observed data
endYr	The ending year of the observed data
modelID	The ID of regression model used for load estimation
r2	R-Squared (%) for the selected LOADEST regression model used to estimate the P load

Note: * only for TP as only point source TP inputs are available.

Our TP load estimates are highly consistent with the WRTDS model with high r^2 and low root mean square error (RMSE) (Fig. 2). The minor disparities observed between these two datasets are likely attributable to variations in temporal coverage. For PO_4^{3-} , we found that only 11 stations with WRTDS estimates matched the stations used here, and all 11 stations are located in small watersheds. Therefore, we leveraged filtered PO_4^{3-} loads estimated by WRTDS to assess if the LOADEST estimated unfiltered PO_4^{3-} loads. Unfiltered PO_4^{3-} measures both the dissolved PO_4^{3-} as well as PO_4^{3-} compounds bound to suspended sediments and organic materials, and thus will have higher load compared to filtered PO_4^{3-} measurements (Fig. S2). Nonetheless, the high correlation indicates our estimates of unfiltered PO_4^{3-} are reasonable.

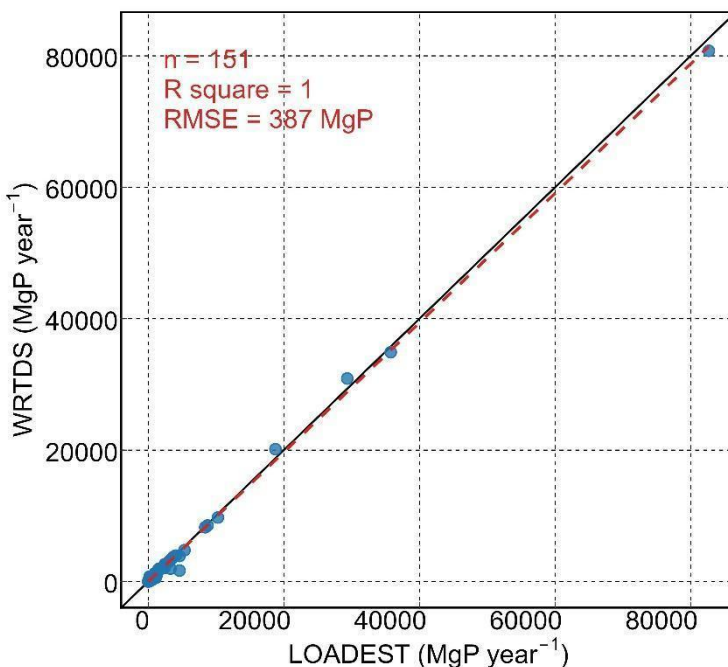


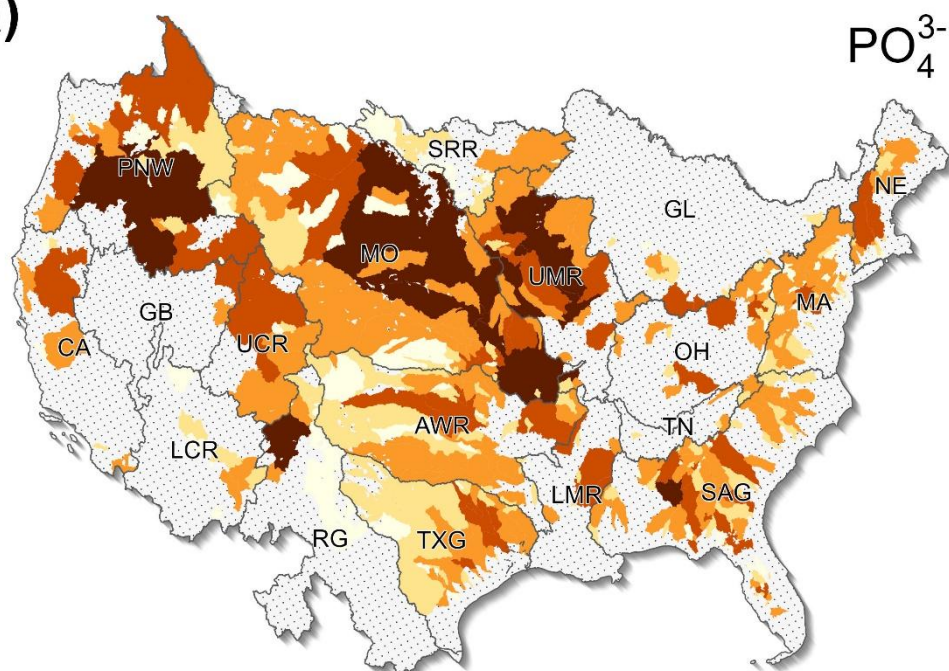


Figure 2: Comparison of riverine TP loads between our estimates and previous WRTDS estimated values at 151 hydrological stations. Note that the riverine TP loads vary greatly at different locations and over time, with most sites being below 10,000 MgP year⁻¹.

Spatial patterns of PO₄³⁻ and TP loads from each HUC group across the CONUS are shown in Fig. 3. Additionally, the location of the hydrologic station at the outlet of each HUC group and the loads of streams in which it is located are shown in Fig. S3. The datasets encompass 547 hydrologic stations/HUC groups for PO₄³⁻ and 1,225 stations/HUC groups for TP, covering 4,894,464 and 6,118,360 km² PO₄³⁻ and TP, respectively. The difference in spatial coverage is mainly due to the abundance of TP compared to PO₄³⁻. Stations with high P loads are predominantly situated in the Midwest or proximate to megacities, with a general pattern of higher P loads observed in the eastern U.S. PO₄³⁻ loads range from 111 to 31,671,885 kgP yr⁻¹ and TP loads range from 235 to 336,223,136 kgP yr⁻¹. Median loads are 76,202 and 108,305 kgP yr⁻¹ and average loads are 436,311 and 1,012,363 kgP yr⁻¹, for PO₄³⁻ and TP, respectively.



(a)



(b)

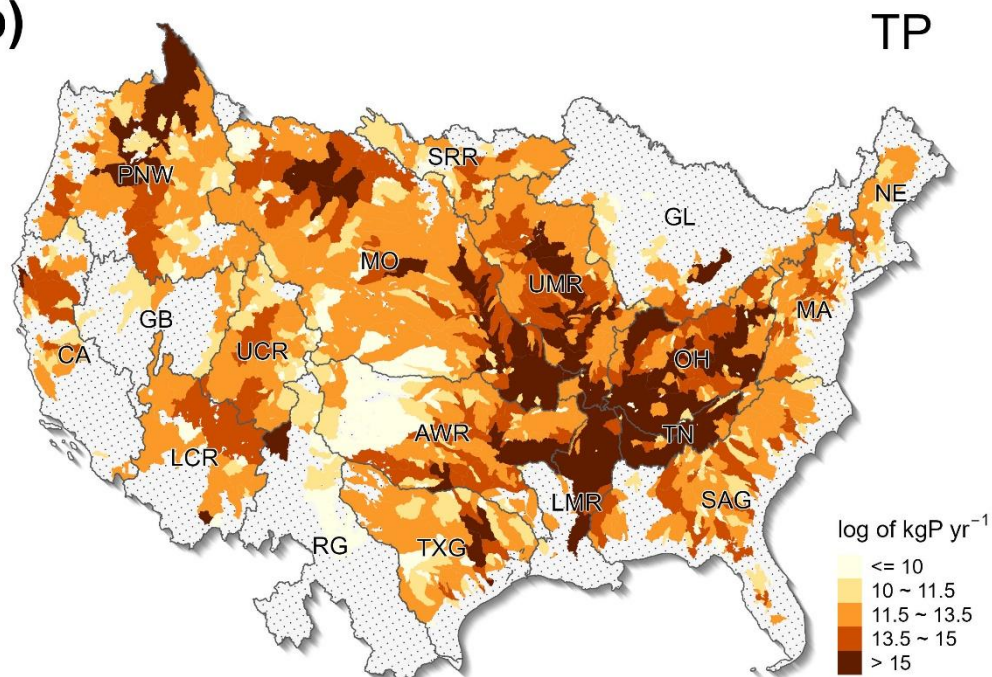




Figure 3: Riverine (a) PO_4^{3-} and (b) TP loads from HUC groups across the CONUS. The boundary lines show the Hydrologic Unit Catalogue 2-digit (HUC2) watersheds. Grey areas indicate regions with no data. For visualization purposes, the logarithm was used here.

The spatial distribution of riverine P gain and loss is shown in Fig. 4. Both PO_4^{3-} and TP gain and loss exhibit similar spatial patterns over the CONUS, with most areas exhibiting riverine P gains. The area-weighted average PO_4^{3-} gain stands at 25.39 $\text{kgP km}^{-2} \text{yr}^{-1}$, and the TP gain is 33.68 $\text{kgP km}^{-2} \text{yr}^{-1}$. Median PO_4^{3-} and TP gains are lower than averages, standing at 16.75 $\text{kgP km}^{-2} \text{yr}^{-1}$ and 33.57 $\text{kgP km}^{-2} \text{yr}^{-1}$, respectively. At the HUC group scale, the highest area-weighted PO_4^{3-} gain was identified in the Upper Mississippi Region (UMR), amounting to about 113.96 $\text{kgP km}^{-2} \text{yr}^{-1}$. The highest TP gain reached 186.55 $\text{kgP km}^{-2} \text{yr}^{-1}$ in the Tennessee Region (TN). Notably, widespread regions in the Midwest exhibit heightened P gains, particularly in terms of PO_4^{3-} , suggesting a discernible impact of human activities (e.g., agricultural fertilization). At the HUC2 level, the lowest area-weighted PO_4^{3-} gain (1.72 $\text{kgP km}^{-2} \text{yr}^{-1}$) was found in the Rio Grande Region (RG), and the lowest TP gain (0.62 $\text{kgP km}^{-2} \text{yr}^{-1}$) was found in the Upper Colorado Region (UCR). Refined examination at the HUC group level showed that, over the CONUS, 392,778 km^2 and 1,468,973 km^2 areas exhibited riverine PO_4^{3-} and TP losses, respectively.

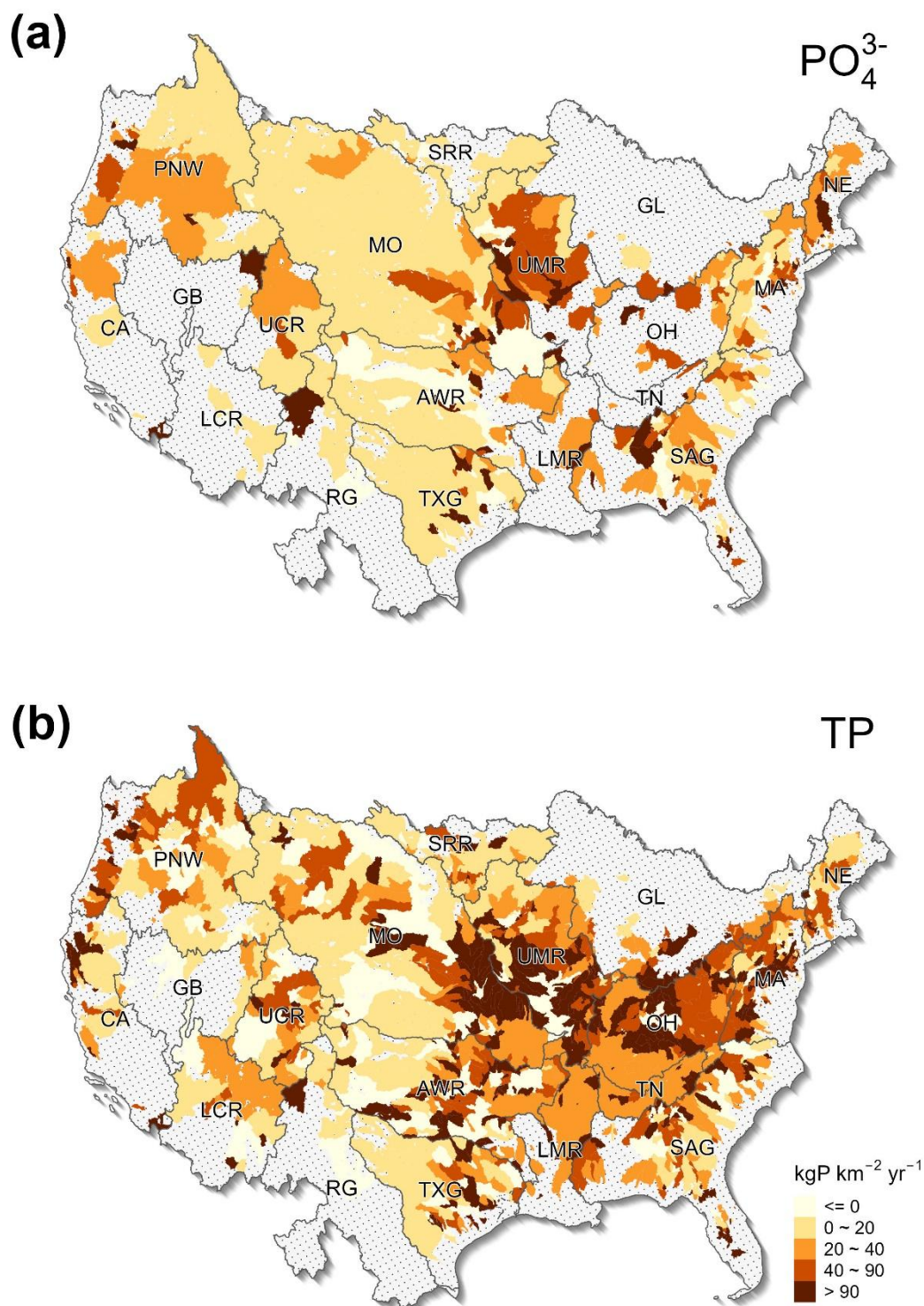




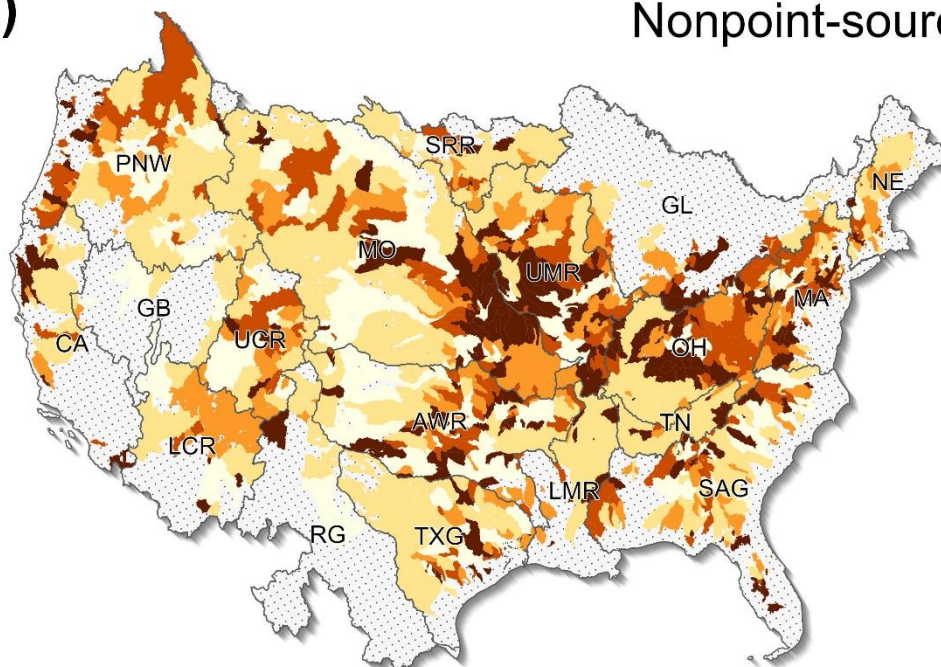
Figure 4: The spatial distribution of the gain and loss in riverine (a) PO_4^{3-} and (b) TP over the CONUS. The boundary lines show the Hydrologic Unit Catalogue 2-digit (HUC2) watersheds. Grey areas indicate regions with no data.

3.2 Point and nonpoint source contributions

We also mapped the spatial point source and nonpoint source inputs of TP, as shown in Fig. 5. The nonpoint source contributions are estimated based on Equation (2), which provides a lower-end estimate given that the riverine removal of point and nonpoint source P as shown in Equation (2) was not considered. Point and nonpoint source contributions to riverine TP pollution exhibited large differences in both the magnitude and spatial distribution. Over the CONUS, the area-averaged point source input of TP is $5.44 \text{ kgP km}^{-2} \text{ yr}^{-1}$. By subtracting point source inputs from the calculated TP gain and loss, we obtained an area-averaged nonpoint source TP contribution of $28.24 \text{ kgP km}^{-2} \text{ yr}^{-1}$. Regions characterized by high TP gain with minimal point source pollution were observed in the Midwest. Notably, in most of the agriculturally intensive Missouri and Tennessee-Ohio river basins, total nonpoint source discharge significantly surpassed point source contributions. Upon the exclusion of point source contributions (Fig. 5b), there is a substantial change, with the areas with riverine TP losses expanding to $1,603,258 \text{ km}^2$, most of them in the Missouri and Arkansas-White-Red River Basins. In general, most watersheds with negative nonpoint sources are concentrated in the western U.S. This does not mean that the nonpoint source P inputs are negative, but indicates that riverine processes likely removed a large fraction of point and nonpoint source P.



(a) Nonpoint-source



(b) Point-source

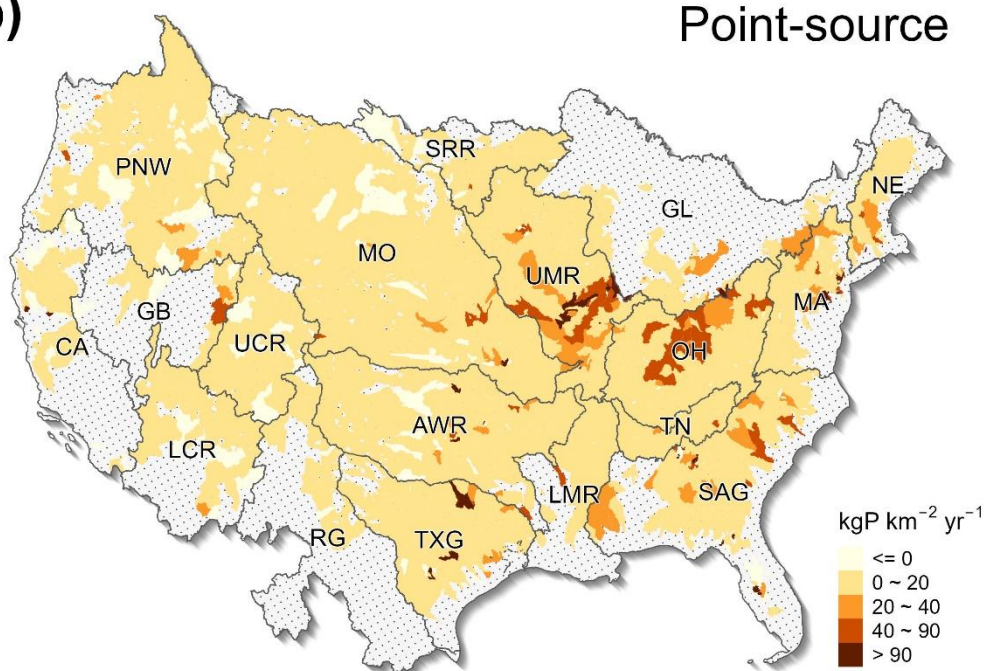




Figure 5: The spatial distribution of (a) nonpoint source and (b) point source contributions to riverine P pollution over the CONUS. The boundary lines show the Hydrologic Unit Catalogue 2-digit (HUC2) watersheds. Grey areas indicate regions with no data.

3.3 Factors influencing TP

We employed a random forest model to assess the influence of climate, land use, human activities, and catchment characteristics on riverine TP gain and loss and TP loads (Fig. 6). Note that the calculated P loads represent the outcome of the entire upstream catchment processes, while the riverine P gain and loss data represent both upstream catchment processes (e.g., P inputs from upstream) and local catchment properties (e.g., climate and land use in a HUC group). Such differences lead to the use of different sets of influencing factors (Fig. 6). The land use, climate and point source factors were calculated for the entire upstream area draining to a hydrological station for TP load analysis. In contrast, those factors were averaged over a HUC group for riverine gain and loss analysis. Additionally, for the analysis of riverine P gain and loss data, we included upstream P inputs. Analysis results indicate that upstream input is the sole statistically significant factor affecting TP gain and loss, with climate and land cover showing no notable impact. Conversely, TP loads are predominantly influenced by climatic factors, alongside significant contributions from point source discharges and urban land use.

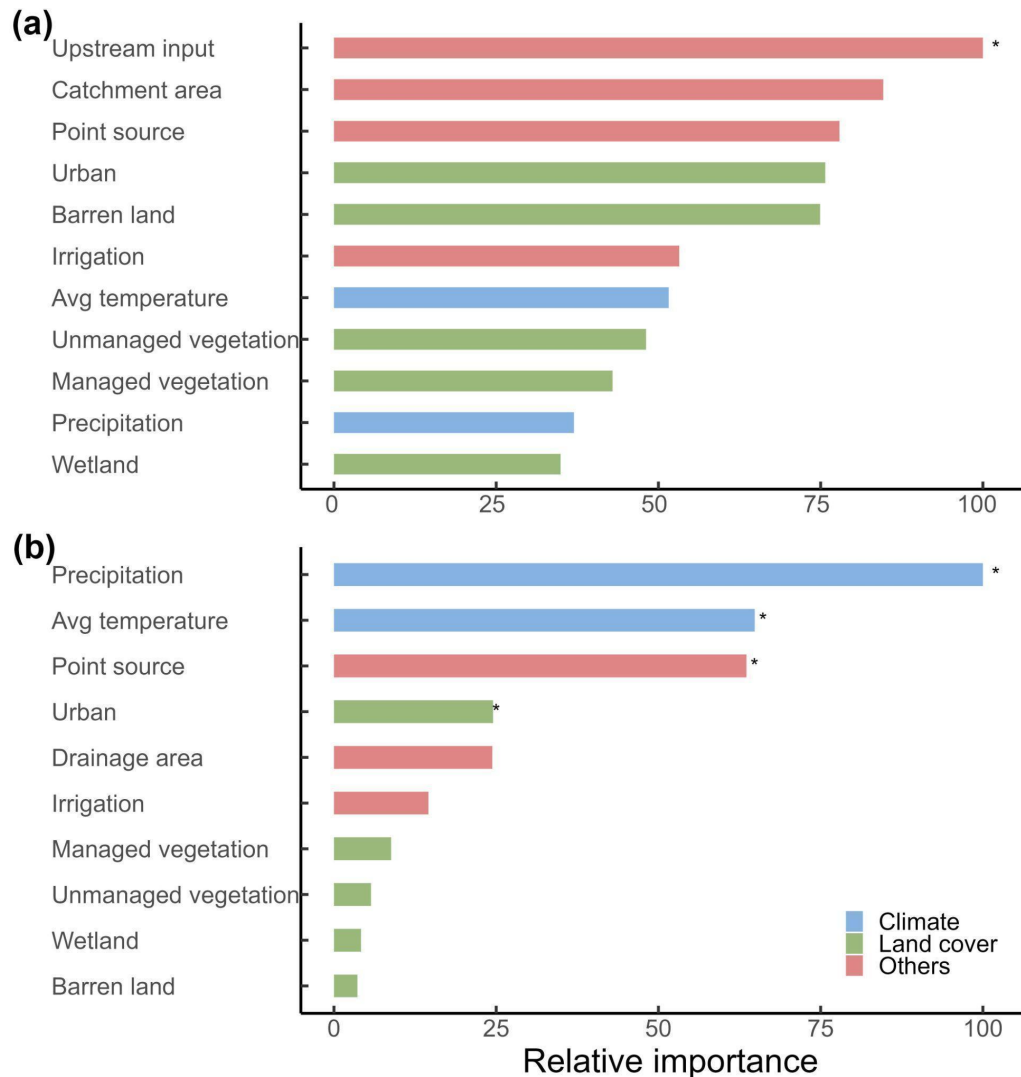


Figure 6: The importance of factors influencing (a) TP gain and loss and (b) TP loads. Asterisks indicate significance at a level of 0.05.

4 Discussion

4.1 Important contributions from nonpoint sources to riverine P pollution

The estimated area-averaged nonpoint source TP contribution ($28.24 \text{ kgP km}^{-2} \text{ yr}^{-1}$) represents a reduction of 16.2% from the calculated TP gain and loss that includes contributions from both point and nonpoint sources ($33.68 \text{ kgP km}^{-2} \text{ yr}^{-1}$). Given that the TP inputs from point and nonpoint sources are often subject to riverine removal (Maavara et al., 2015), the estimated nonpoint source TP based on Equation (1) should be augmented by the amount of total TP inputs (including both nonpoint and point source) removed through riverine processes. Therefore, the calculated nonpoint source inputs of TP represent an



underestimate of the contributions from nonpoint sources. If we assume a 12% removal rate for TP inputs (Maavara et al., 2015), then the nonpoint source inputs of TP would increase from 28.24 kgP km⁻² yr⁻¹ to 32.28 kgP km⁻² yr⁻¹. Collectively, the results show that the nonpoint sources likely contribute more than 84% of riverine TP pollution.

4.2 Implications for analysing environmental controls of riverine P

Climatic factors were key drivers of TP loads at the outlet of a watershed, which in general aligns with findings from previous studies (Sabo et al., 2023) and underscores the role of climate in nutrient transport dynamics. Our environmental control analysis using the gain and loss data showed that upstream inputs are leading control of local riverine gain and loss (Fig. 6a), in addition to local inputs of P from point and nonpoint sources and local riverine processes, such as in-stream retention through mechanisms such as P absorption by periphyton via photosynthesis and hydrological processes like reduced streamflow and sedimentation (Dodds, 2003; Withers and Jarvie, 2008). Notably, although accumulated agricultural P inputs (i.e., livestock waste and agricultural fertilizer) positively influenced TP gain and loss (Fig. S4), they were not included in this analysis due to mismatch of spatial scales. In general, using TP loads and riverine P gain and loss can lead to pronounced differences in the analysis of importance of environmental controls. Although climate conditions (i.e., precipitation and temperature) are the major controls of TP loads, which represent the integration of the entire watershed conditions, while riverine P gain and loss indicate that the amount of upstream P inputs entering a local catchment is an important factor influencing the riverine processing of P.

Both the differences and the analysis using TP loads and riverine gain and loss data revealed the importance of urban land and agricultural management. For example, both analyses show that irrigation can influence riverine TP, indicating that improving irrigation efficiency and technology holds potential to reduce TP inputs from cropland fertilization (Xia et al., 2020). Though we didn't assess factors influencing PO₄³⁻ due to the lack of point source PO₄³⁻ data, TP hotspots are expected to occur further downstream than PO₄³⁻ hotspots (Fig. 3). This is probably because rivers typically can retain (e.g., periphyton assimilation, adsorption onto suspended or bed sediment) a considerable proportion of incoming soluble-reactive P (e.g., PO₄³⁻) within the upper network, whereas particulate P continue to transport to downstream (Jarvie et al., 2012; Robertson and Saad, 2019; Royer et al., 2006b). Overall, the intricate interplay between climate and land use factors underscores the complex nature of P dynamics in riverine systems. These newly developed riverine gain and loss datasets help improve understanding of local controls of riverine P dynamics and identify hotspots of changes in riverine P.

4.3 Limitations and contribution

While the newly developed datasets leverage upstream-downstream topology information at the HUC12 level to help increase the spatial resolution of riverine P gain and loss data, it is essential to acknowledge limitations relevant to understanding and quantifying P cycles and identifying sources of P inputs. First, the accuracy of load estimation via LOADEST is contingent upon the availability of paired P concentration data from hydrological stations. Stations with limited observations may



introduce higher uncertainties in load estimations. The robustness of our datasets is partially reflected in the number of observations available. The average and median numbers of PO_4^{3-} observations per site is 54 and 29, respectively; for TP, the average and median numbers of observations per site is 134 and 90, respectively. In addition, the average center year of TP observations is 1992, with a median of 1991, while for PO_4^{3-} , the overall observation time is relatively early, with an average of 1981 and a median of 1980. The use of AIC to choose the most parsimonious regression model (average r^2 of 0.76 and 0.83 for PO_4^{3-} and TP, respectively) helped reduce uncertainties in load estimates.

Additionally, we calculated the P loads by averaging over different time periods with available data for each hydrological station. The mismatch between observational periods of upstream and downstream hydrological stations could introduce uncertainties, given that the available data cover various time periods for different hydrological stations. For example, streamflow discharge, which is important for calculating nutrient loads, can vary from year to year. Here, we assumed that multi-year average estimates of P loads are representative of the long-term pattern at a hydrological station. This may not hold for some upstream and downstream stations covering time periods that do not overlap with each other. Therefore, we provided the number and period of observations and model performance information in the datasets, which can help users to refine the calculation of riverine P gain and loss by further screening the P loads data at the hydrological stations. Note that available hydrologic stations with observed P concentration and streamflow data are relatively sparse in the western vs. eastern U.S., particularly for PO_4^{3-} . This led to large gaps in the spatial coverage of the datasets (Fig. 4). Increasing the number of hydrological stations with P observations holds the potential to enhance the accuracy of riverine P estimates in the future.

It is also worth noting that the calculated contribution of TP from nonpoint sources represents a conservative estimate, given the unknown rate of TP removal from point and nonpoint sources. Although previous studies showed that TP removal rates were generally small, they could vary substantially across regions, as evidenced by the areas with riverine P loss (Fig. 4). It is reasonable to assume that the estimated TP contribution from nonpoint sources is greater than 84% over the CONUS; however, the local TP contribution from nonpoint sources could be much lower, particularly in regions with high point source inputs. Also, the removal rates of P from point and nonpoint sources are likely different due to differences in the quality of P inputs (e.g., biodegradability and adsorption and desorption to sediments) and flow pathways (Wang et al., 2025). Therefore, caution should be taken when interpreting the local contribution to P pollution from nonpoint sources.

Despite these challenges, our datasets make a unique contribution to the quantification and analysis of riverine P load, gain and loss, and sources across the CONUS. They can support the evaluation and diagnosis of large-scale watershed models, the examination of environmental controls on riverine P loads, and the estimation of contributions to P gain and loss. The insights derived from our datasets contribute to a more comprehensive understanding of P dynamics, providing a foundation for improved water quality management on local, regional, and national scales.



5 Code and data availability

All codes for validating and visualizing PO_4^{3-} and TP gain and loss from the load estimations were run in R version 4.3.1 and are archived at https://github.com/ymwang4924/gain-loss_P. The datasets presented in the paper are available at <https://doi.org/10.6084/m9.figshare.28509317> (Wang et al., 2025).

6 Conclusions

In this study, we estimated riverine loads of PO_4^{3-} and TP and derived their gain and loss across the CONUS, leveraging the upstream-downstream hydrological connectivity information contained in the NHDPlus catchment map. On average, rivers across the CONUS gain TP at a rate of $33.68 \text{ kgP km}^{-2} \text{ yr}^{-1}$, with notable hotspots in the Midwest. Due to the limitations of data availability, the precision of estimated P gain and loss data could be influenced by the number and periods of observations available at upstream and downstream stations. We provided additional information regarding the number of observations available, temporal coverage of data, the regression model used, and the model's statistical performance, so that users can further subset the datasets to meet certain specific criteria.

The riverine P gain and loss datasets allow the estimation of riverine P removal or accrual at a refined spatial resolution to better reflect the impacts of local controls. In contrast, riverine P loads at hydrological stations embody the integrated processes from the entire area upstream of a specific station. Also, by combining point source inputs with the riverine P gain and loss datasets, we derived conservative estimates of the contribution of nonpoint sources to riverine TP ($28.24 \text{ kgP km}^{-2} \text{ yr}^{-1}$). The control factor analysis with a random forest model demonstrated that upstream inputs had the greatest influence on the local riverine P gain and loss, while climatic factors dominated riverine P loads at hydrological stations. This suggests that nutrient management practices that prioritize enhancing irrigation efficiency and integrating strategies such as targeted fertilizer application and wetland restoration may more effectively capture and reduce phosphorus mobilization from agricultural lands. The newly developed riverine P datasets in this study extend utility to diverse applications, encompassing, but not limited to, the evaluation of watershed models, identification of critical source areas, and optimization of agricultural management strategies. Future studies may concentrate on filling gaps in the spatial and temporal coverage of the datasets (particularly for PO_4^{3-}).

Author contributions

Y.W.: Conceptualization, methodology, investigation, formal analysis, data curation, visualization, and writing—original draft. **X.Z.:** Conceptualization, methodology, investigation, writing—original draft, writing—review and editing, supervision, project administration, and funding acquisition. **K.Z.:** methodology, investigation, writing—review and editing. **R.D.S.:** investigation, writing—review and editing. **Y.M.:** visualization, writing—review and editing. **C.M.C.:** writing—review and editing.



324 **Competing interests**

325 At least one of the (co-)authors is a member of the editorial board of *Earth System Science Data*.

326 **Disclaimer**

327 The views expressed are those of the authors, and do not necessarily represent the views or policies of the U.S. Environmental
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