Received: 10 June 2024 | Accepted: 24 October 2024

DOI: 10.1111/1752-1688.13243

RESEARCH ARTICLE

AMERICAN WATER RESOURCES ASSOCIATION JAWRA Journal of the American Water Resources Association

Predicting lake chlorophyll from stream phosphorus concentrations

Lester L. Yuan | **Michael J. Paul**

Office of Water, U.S. Environmental Protection Agency, Washington, District of Columbia, USA

Correspondence
Lester L. Yuan, Office of Water, U.S. Environmental Protection Agency, 1200 Pennsylvania Ave NW, Mail Code 4304T, Washington, DC 20460, USA.
Email: yuan.lester@epa.gov

Abstract

Excess nutrient loads from streams drive primary production in downstream lakes, and managing these loads is key to achieving desired conditions in lakes. However, quantifying nutrient loads requires intensive sampling of both nutrient concentrations and streamflow. Total phosphorus measurements collected during routine stream monitoring are broadly available, but these data are thought to provide little information on annual nutrient loads because they are typically collected during low, baseflow conditions. Here, we demonstrate that these routine phosphorus measurements are correlated with annual nutrient loads. We also show that the average of these routine measurements of stream phosphorus within a watershed predict the average lake chlorophyll concentration in that same watershed. These relationships can then be used to set targets for stream phosphorus concentrations to achieve desired conditions in lakes.

KEYWORDS
phosphorus load, lake eutrophication, routine monitoring, nutrient criteria

1 | INTRODUCTION

Streams regulate the downstream transport of terrestrially derived nutrients (Tank et al., 2008). Uptake and mineralization of nutrients in streams involves cycling between the benthos and water column, resulting in spiraling of nutrients downstream (Hall et al., 1998; Meyer & Likens, 1979; Mulholland et al., 1985, 1997; Newbold et al., 1983; Payn et al., 2005; Valett et al., 1996; Webster et al., 2003). The uptake of both nitrogen and phosphorus is driven by abiotic and biotic drivers like sorption, microbial demand, and primary production (Griffiths & Johnson, 2018; Hall et al., 2002; Meyer, 1979). This uptake scales with stream size or discharge but can vary depending on the nutrient species (Hall et al., 2013; Tank et al., 2008). Importantly, nutrient uptake tends to scale with nutrient loading and nutrient concentration (Dodds et al., 2002). However, at high concentrations, nutrient uptake becomes saturated and insufficient to balance increased anthropogenic nutrient loads (Alexander et al., 2007; Bernot & Dodds, 2005); hence, nutrient concentrations and loads often increase with increasing human land use and population density (Caraco & Cole, 1999; Howarth et al., 1996). Declines in stream processing efficiency and concomitant increases in downstream export have implications for both streams themselves and downstream ecosystems such as estuaries and lakes.

Algal biomass in lakes is driven by nutrient loads. That is, when nutrient loads increase, algal biomass in most lakes also increases (Dillon & Rigler, 1974; Filstrup et al., 2014; Smith, 1982), and this relationship has been found to hold for both nitrogen and phosphorus (Lewis & Wurtsbaugh, 2008; Quinlan et al., 2021; Smith, 1982). Increased algal biomass is linked to other adverse conditions in lakes such as reduced

Paper No. JAWR-24-0075-P of the *Journal of the American Water Resources Association* (JAWR).

Discussions are open until six months from publication.

Research Impact Statement

This paper demonstrates that measurements of total phosphorus collected in streams during routine monitoring predict chlorophyll concentrations in lakes, informing development of nutrient criteria.

water clarity, increased anoxia or hypoxia, and increases in the proportion of cyanobacteria and the toxins they produce. Many of the latter present risks for wildlife and human health.

Accurately quantifying nutrient loads requires frequent (e.g., daily) concurrent measurements of streamflow and nutrient concentrations (Johnes, 2007), and the difficulty of acquiring these data has limited the availability of load information. In contrast, single, instantaneous measurements of nutrient concentrations are broadly available as these data are frequently gathered as part of routine monitoring conducted by state and federal agencies. Monitoring protocols typically specify that samples are collected during baseflow conditions, but in most streams, nutrient loads are mostly transported during high stream flows (Novak et al., 2003). Phosphorus loads, in particular, can be sensitive to stream flow because much of the phosphorus in a stream is sorbed to particulate material, which is mobilized to varying degrees during high flows (Banner et al., 2009). Therefore, measurements of nutrient concentrations collected during routine monitoring generally do not provide quantitative estimates of nutrient loads at specific sites. However, it is possible that, across many sites, baseflow measurements of nutrients provide an indication of the relative magnitudes of nutrient loads. Based on this idea, we hypothesized that baseflow total phosphorus (TP) concentrations are correlated with nutrient loads. Because of this correlation, we further hypothesized that average stream concentrations measured during routine monitoring within a watershed predict lake chlorophyll concentrations within that same watershed. We tested these hypotheses using data from the state of Minnesota and using data from a continental spatial scale. We then placed the results of our analysis in the context of their utility for informing the development of targets for stream nutrient concentrations to achieve management goals in downstream lakes.

2 | MATERIALS AND METHODS

2.1 | Data

We downloaded nutrient load data collected by Minnesota's Watershed Pollutant Load Monitoring Network (MNPCA, 2019) in 2017–2020. Approximately 200 streams are included in this network and are intensively sampled, particularly during storm events, to characterize pollutant loads. Load models relating pollutant concentrations to streamflow are fit for each site and used to estimate annual pollutant loads, which are reported as an annual flow-weighted concentration of TP for each site ($TP_{flow\ weighted}$). We summarized these concentrations as the geometric mean $TP_{flow\ weighted}$ for 2017–2020 for each site and designated these data as the “load database”. For each site, we also extracted the in-stream TP concentration corresponding to the lowest recorded flow from 2017 to 2020 and used this value as an estimate for the baseflow TP concentration at each site ($TP_{baseflow}$).

We also downloaded routine monitoring data for TP concentrations in streams and chlorophyll *a* (Chl) concentrations in lakes in Minnesota from the Water Quality Portal, restricting our queries to samples collected in summers (June–August) of 2017–2020. Lakes in this dataset were selected using a rotating basin design, such that over a 10-year period, all recreation lakes larger than 200 ha and a portion of all publicly accessibly lakes greater than 40 ha were sampled. We designated these data as the “sample database”. We matched sample locations to 12-digit hydrological unit codes (HUCs) downloaded from https://hub.arcgis.com/datasets/mpca::huc-12-state-of-minnesota/explore. Specific field protocols are described elsewhere (Heiskary & Bouchard, 2015; MNPCA, 2023a, 2023b).

We assembled continental-scale data for lakes and streams from the USEPA National Lakes Assessment (2007 and 2012) and from the USEPA National Rivers and Streams Assessment (2008–2009, 2013–2014). Lakes greater than 4 ha in 2007 and 1 ha in 2012 were selected using a stratified random sampling design. Details for the sampling and laboratory protocols for these surveys are provided elsewhere (USEPA, 2011, 2012, 2013), so here we only provide information regarding the parameters used in this analysis. For lakes, water samples were collected near the surface with an integrated sampling device. Samples were filtered in the field with glass fiber filters, and Chl measured in the lab. For streams, water samples were collected in the flowing portion of the stream near the center and returned to the lab. There, TP concentrations were measured to pre-specified levels of precision. The 8-digit HUC associated with each sample was provided in the national datasets, so for national-scale analysis we selected 8-digit HUCs as the spatial scale of the analysis.

2.2 | Statistical analyses

We used the Minnesota TP load data to test our hypothesis that across many sites, baseflow TP concentrations are correlated with TP loads by examining the relationship between $TP_{baseflow}$ and $TP_{flow\text{-}weighted}$. We next tested whether mean TP collected during routine monitoring in each 12-digit HUC is correlated with annual TP load. To compare mean TP in each 12-digit HUC (TP_{HUC}) to TP loads, we first excluded data from the MN sample database that were included in the MN load database to ensure that the calculation of mean TP in any HUC was not affected by measurements used to compute TP loads. For the remaining sample data, we randomly selected one TP measurement from each site in the sample database to avoid overweighting sites with multiple samples. We then identified the 12-digit HUC where the site for each flow-weighted TP concentration was located, calculated the geometric mean TP concentration from the sample database for sites located within the same HUC (i.e., TP_{HUC}). We then examined the relationship between TP_{HUC} to $TP_{flow\ weighted}$.

We used a hierarchical Bayesian model to represent the relationship between mean TP in streams in a HUC from the Minnesota sample database and average Chl in lakes in the same HUC. Applying a hierarchical model provided two benefits. First, the uncertainty in the estimates of mean values for TP and Chl for each HUC varied because of differences in the number of samples available, and the hierarchical model provided a robust framework for accounting for the effects of these differences among HUCs. Second, the model allowed us to partition the variance in observations of Chl among three levels of organization: (1) temporal variability of Chl within individual lakes, (2) spatial variability of mean Chl among lakes within a HUC, and (3) variability of mean Chl among HUCs in the full dataset.

Initial exploratory analysis suggested that a logistic function best represented the relationship between stream TP and lake Chl, and so we specified the following relationship between the mean of ln(Chl) in lakes in a HUC (Chl_{HUC}) and the mean ln(TP) in streams located in the same HUC (i.e., TP_{HUC}):

$$\ln\left(\mathrm{Chl_{HUC}}\right) = b_1 + \frac{\left(b_2 - b_1\right)}{1 + \exp\left(-k\ln\left(\mathrm{TP_{HUC}}\right) - p_0\right)} + \epsilon, \tag{1}$$

where b_1, b_2, k, and p_0 are model parameters estimated from the data, and ϵ is a normally distributed error term with a standard deviation of σ_1.

Mean Chl concentrations in individual lakes (Chl_{lake}) were modeled as being normally distributed about the mean value for the HUC in which the lake is located:

$$\ln\left(\mathrm{Chl}_{\mathrm{lake},j,k[j]}\right) \sim \mathrm{Normal}\left(\ln\left(\mathrm{Chl}_{\mathrm{HUC},k}\right), \sigma_2\right), \tag{2}$$

where the index, j, refers to different lakes, and the index, k, refers to different HUCs. The parameter, σ_2, is the standard deviation of lake means about the mean for the HUC. Then, individual measurements of ln(Chl_{obs}) were modeled as being normally distributed about the mean for each lake:

$$\ln\left(\mathrm{Chl}_{\mathrm{obs},i,j[i]}\right) \sim \mathrm{Normal}\left(\ln\left(\mathrm{Chl}_{\mathrm{lake},j}\right), \sigma_3\right), \tag{3}$$

where the index, i, refers to individual measurements, and σ_3 is the standard deviation of measurements collected within each lake.

Individual TP measurements were modeled as being normally distributed about the mean for the HUC in which the stream is located:

$$\ln\left(\mathrm{TP}_{\mathrm{obs},i,k[i]}\right) \sim \mathrm{Normal}\left(\ln\left(\mathrm{TP}_{\mathrm{HUC},k}\right), \sigma_4\right). \tag{4}$$

We fit this model to sample database using the statistical modeling software package, stan (Stan Development Team, 2016). (The stan code is provided in supplemental information.) We fit the same model to the national data, but because a limited number of repeat measurements were available in these lakes, we partitioned Chl measurements at only two levels of organization (site and HUC) and did not attempt to estimate the temporal variability of Chl. In all other respects, the national model was identical to the model for MN.

3 | RESULTS

TP load estimates were available at 198 sites in MN. Baseflow TP concentrations were correlated with flow-weighted TP concentrations at these sites (r=0.67, Figure 1). Flow-weighted concentrations were mostly greater than baseflow concentrations, as would be expected. At a few sites, baseflow TP concentrations exceeded flow-weighted concentrations, indicating that TP concentrations were affected by point source loads of TP, such that measured concentrations of TP decreased with increased flow due to dilution (Yuan, 2022). The variability in differences between flow-weighted and baseflow concentrations was greatest in the middle of TP gradient (baseflow TP concentrations ranging from 20 to 80 µg/L).

A total of 64 12-digit HUCs in MN had both load estimates and monitored values of TP (exclusive of the site where the load was estimated). In these HUCs, $TP_{flow\text{-}weighted}$ concentrations were moderately correlated with TP_{HUC} (r=0.72, Figure 2). As with the comparison between $TP_{baseflow}$ and $TP_{flow\text{-}weighted}$, the greatest differences between TP_{HUC} and $TP_{flow\text{-}weighted}$ concentrations were observed in the middle of the TP gradient.

In the MN dataset, 7133 measurements of lake Chl were available, collected from 867 lakes and 263 12-digit HUCs. In those same HUCs, after randomly selecting a single sample from each site, a total of 645 TP samples were available. Sampled lakes were distributed across the state.

Chl_{HUC} was accurately predicted as a logistic function of TP_{HUC} in the MN data (Figure 3). Lake Chl_{HUC} initially increases with increased TP_{HUC}, but at high concentrations of TP_{HUC} the slope of the relationship approached zero. The standard deviation of ln-transformed Chl_{HUC} about this mean relationship was 0.49 (σ_1 in Equation 1). Other components of variance in Chl measurements were larger: the standard deviation of ln-transformed mean lake Chl about the HUC mean was 0.76 (σ_2 in Equation 2), and the standard deviation of ln-transformed measurements of Chl within the same lake was 0.72 (σ_3 in Equation 3). The total variance of Chl measurements about the HUC mean was 1.10 ($0.76^2+0.72^2$).

The relationship between stream TP and lake Chl can potentially be used to set targets for stream TP to achieve desired concentrations of Chl in lakes. To that end, the prediction intervals displayed in Figure 3 are calculated based on the variance among HUCs and among sites within each HUC. Hence, the prediction intervals capture the range of mean Chl values in lakes one would expect, given a mean TP concentration in a HUC. Variance associated with Chl measurements within individual lakes is not included because desired conditions in lakes are usually expressed in terms of seasonal or long-term mean values of Chl.

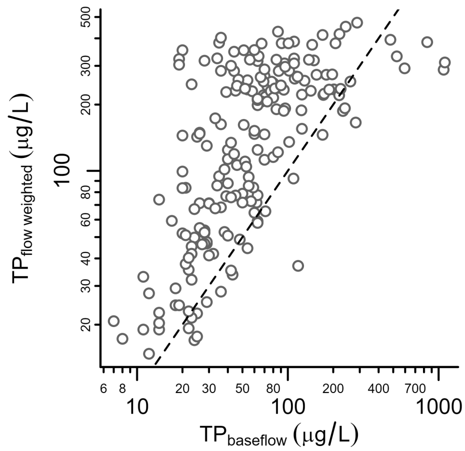

FIGURE 1 Baseflow total phosphorus (TP) ($TP_{baseflow}$) versus flow-weighted TP ($TP_{flow\ weighted}$) concentrations at the same sites. Dashed line: 1:1 relationship.

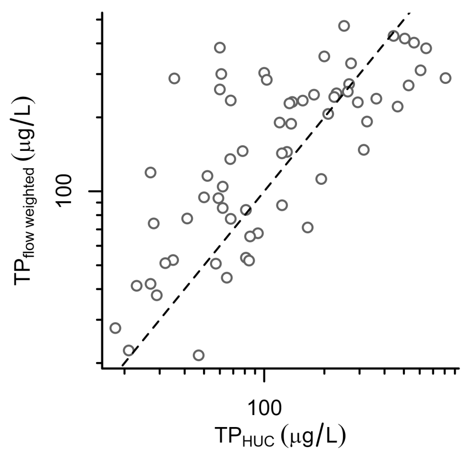

FIGURE 2 Geometric mean TP within a 12-digit hydrological unit code (HUC) (TP_{HUC}) versus $TP_{flow\ weighted}$ concentration for one site located within the same 12-digit HUC. Dashed line: 1:1 relationship.

AMERICAN WATER RESOURCES ASSOCIATION JAWRA JOURNAL OF THE AMERICAN WATER RESOURCES ASSOCIATION

In the national dataset, 2821 measurements of lake Chl and 2444 measurements of stream TP were available, collected from 674 8-digit HUCs evenly distributed across the conterminous U.S. Chl_{HUC} was accurately predicted as a logistic function of TP_{HUC} in the national dataset (Figure 4). The mean relationship estimated for the national data were statistically indistinguishable from the relationship estimated in MN (solid lines in Figure 4).

The estimated standard deviation of Chl_{HUC} about this mean relationship was 0.68. This value is greater than observed in MN likely because of the greater heterogeneity among HUCs at the larger spatial scale. The standard deviation of variations in ln-transformed Chl measurements about the average for the HUC was 0.99, a value that includes contributions from both among-lake differences within each HUC and temporal variability within each lake. The variance associated with this standard deviation is 0.98, a value that is similar to the combined variance of the same two partitions of variability in the MN data.

4 | DISCUSSION

Nutrient pollution is consistently ranked as one of the leading causes of degraded water quality in the world, contributing to responses that include hypoxia/anoxia, habitat loss, food web shifts, nuisance growths, aesthetic impacts, and harmful cyanobacterial blooms and cyanotoxins. Total nitrogen and TP were identified as the most widespread stressors in US lakes (USEPA, 2022), with approximately 46% of lakes assessed as having elevated concentrations of these nutrients. The same study found that TP was the stressor that posed the greatest relative risk,

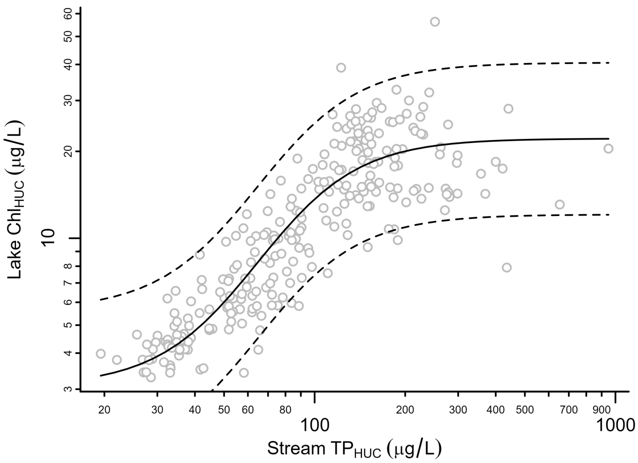

FIGURE 3 TP_{HUC} versus Chl_{HUC} in Minnesota. Solid line: Mean logistic relationship. Dashed lines: 50% prediction interval, accounting for variance among HUCs and among lakes within a HUC.

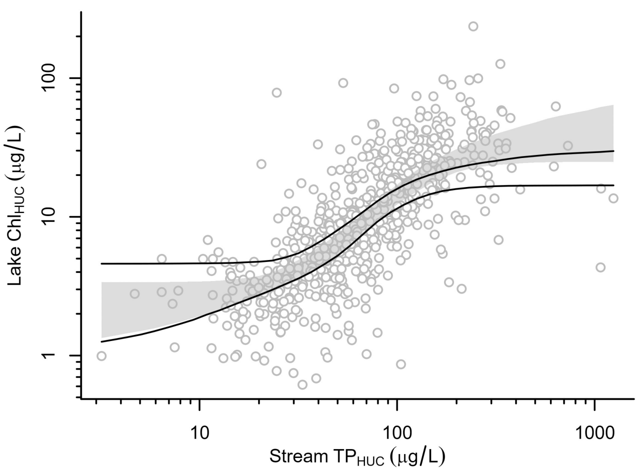

FIGURE 4 TP_{HUC} versus Chl_{HUC} (national data). Shaded area: 95% credible interval for mean relationship estimated from national data, solid lines: 95% credible interval for mean relationship estimated from Minnesota data (see Figure 3).

such that lakes with elevated concentrations of TP were 2.3 times more likely to also have poor biological conditions. Quantitative targets for reducing TP concentrations in tributary streams and rivers would be useful for informing plans to improve lake water quality.

We have shown that mean stream TP concentrations in a watershed predicted mean lake Chl concentrations in that same watershed. We have further found that the relationships estimated between TP and Chl at two disparate spatial scales were statistically indistinguishable from one another. These consistent relationships occurred despite the extensive sequence of causal steps linking stream TP to lake Chl and the variety of outcomes associated with each step. Here, we consider the possible reasons for the effectiveness of our model and the potential applications of these results.

The correlation between baseflow TP concentrations (typically observed during routine monitoring) and flow-weighted TP is the primary reason for the TP_{HUC}–Chl_{HUC} relationship we observed. As noted earlier, the dependence of lake Chl on nutrient loads has been well established (Rast et al., 1983; Vollenweider & Kerekes, 1982). Furthermore, it is understood that a single measurement of TP concentration, particularly at baseflow, provides a poor estimate of annual load at that site. Indeed, at individual sites, we observed that $TP_{flow\text{-}weighted}$ ranged from 1 to 16 times $TP_{baseflow}$ concentration. However, across a gradient of conditions, our analysis has demonstrated that we only require that baseflow concentrations are correlated to loads to effectively predict lake Chl from stream TP, a much less stringent requirement of the data. The uncertainty inherent in translating mean watershed TP to an annual TP load contributes to the uncertainty in the TP_{HUC}–Chl_{HUC} relationship, but notably, the magnitude of this uncertainty was less than the variability of individual lake Chl within a HUC. Furthermore, the consistency of the TP_{HUC}–Chl_{HUC} relationships across disparate spatial scales suggests that the correlation between baseflow and flow-weighted TP may be robust to changes in location.

The correlation between baseflow TP concentrations and flow-weighted TP concentrations suggests that some mechanism connects low flow to high flow nutrient concentrations. One possible explanation is the buffering effect of stream sediments, in which sediments adsorb phosphorus when concentrations are high and release phosphorus at relatively low concentrations, especially as biological activity depletes phosphorus in the water column. Hence, baseflow concentrations reflect the long-term loading patterns (Haggard et al., 2007). Also, the overall relationship between baseflow and flow-weighted TP was anchored by a strong relationship between the two values when baseflow concentrations were less than ~20 μg/L. At these low concentrations, $TP_{flow\ weighted}$ was strongly correlated with $TP_{baseflow}$. Others have observed that the contrast between nutrient concentrations during high and low flows was smaller in undisturbed, low nutrient catchments compared to catchments with higher nutrient loads (Kunimatsu et al., 1999).

A variety of factors control how nutrient loads are expressed as changes in lake productivity, but variations among individual lakes do not affect the relationship we estimated at the watershed scale. Characteristics of lake morphology such as depth, stratification, and retention time status exert strong effects on how nutrient loads are related to changes in Chl (Fee, 1979; Vollenweider & Kerekes, 1982). Differences in water clarity also affect productivity (Wagner et al., 2020), and different lakes also may be expected to have differences in internal loads of nutrients that can affect the degree to which external nutrient loads change Chl (Soranno et al., 1997). In short, differences among lakes can drastically alter how a given nutrient load translates to a Chl concentration. However, for this analysis, the variability in the responses of individual lakes to TP loads is taken into account as a residual variability that is distinct from the uncertainty in the overall relationship between HUC-averaged stream TP and lake Chl. That is, by predicting the mean Chl in a HUC, we averaged out differences among lakes and focused the analysis on large-scale patterns between stream TP and lake Chl. Of course, characteristics of an individual lake need to be considered if one is interested in predictions for that lake, but this analysis suggests that TP loads can be usefully estimated at the watershed scale.

Seminal studies on lake eutrophication linked estimates of nutrient loads to lake Chl (Dillon & Rigler, 1974; Rast et al., 1983; Vollenweider & Kerekes, 1982), but the estimates of nutrient loads were difficult to obtain and hence, the number of lakes included in those models was small. Our approach provides a way to vastly broaden the range of applicability of predictive models for lake Chl. Considering this broader range of conditions indicated that the linear relationship between nutrient load and Chl may saturate at very high loads. At very low concentrations of stream TP, we also observed a weak increase in lake Chl, but additional data at these concentrations are necessary.

Aggregating measurements of stream TP at the watershed scale also increased the sample size from which we could estimate mean TP concentrations, and thus, reduced the influence of single, anomalous measurements. Others have also observed that nutrient load estimates from individual streams can be highly uncertain, but that average loads across a basin can be more precisely quantified (Wellen et al., 2014). We also limited our analysis to a single TP sample from each stream site whereas in the MN data and in other datasets, repeat measurements are often available. Incorporation of these additional measurements would further improve the precision with which watershed mean TP can be quantified.

Water quality standards are a principal mechanism by which US waters are protected from pollution. These standards consist of the designated uses of a waterbody, criteria that protect those uses, and policies to prevent degradation. Numeric criteria are developed to protect uses using a variety of approaches, including dose–response models that link pollutant concentrations to adverse response conditions. Importantly, water quality criteria must not only protect uses in situ (e.g., in a stream) but also downstream (e.g., a downstream lake). For nutrient criteria, stressor-response models have often relied on empirical relationships between nutrient conditions and adverse ecosystem responses, but usually only for in situ relationships and almost never by relating downstream use endpoints to upstream concentrations (USEPA, 2010). The current analysis provides a direct estimate of the TP concentrations in streams that are associated with a specific mean lake Chl target. This estimate can provide a starting point for establishing stream nutrient criteria to maintain or improve lake conditions in a watershed. The watershed scale of this analysis is particularly well suited for states and regions that focus on watersheds when managing water resources (Lintern et al., 2020).

 AMERICAN WATER RESOURCES ASSOCIATION JAWRA JOURNAL OF THE AMERICAN WATER RESOURCES ASSOCIATION

Further work can address some of the uncertainties remaining in this model. First, repeating this work in other locations would broaden confidence in the applicability of these results. In particular, application of the approach in different regions could potentially highlight scenarios in which the current method yields inaccurate predictions. The availability of monitoring data is key to this effort. Our approach of grouping by HUC allowed the use of existing monitoring data, and monitoring datasets in other locations may be dense enough to repeat this analysis. Alternatively, a targeted effort to measure nutrient concentrations in streams and Chl in downstream lakes would permit a deeper exploration of factors that influence the TP-Chl relationship. Other nutrient species (e.g., nitrogen) are also associated with increased lake productivity (Lewis et al., 2011; Paerl et al., 2016), and the current analysis is readily adaptable to quantify their effects.

AUTHOR CONTRIBUTIONS

Lester L. Yuan: Conceptualization; data curation; formal analysis; investigation; methodology; software; validation; visualization; writing – original draft. **Michael J. Paul:** Writing – original draft; writing – review and editing.

ACKNOWLEDGMENTS

The authors gratefully acknowledge the data collection efforts of the Minnesota Pollution Control Agency and the sampling crews for the National Rivers and Streams Assessment and the National Lakes Assessment. Comments from G. Kaufman and B. Walsh greatly improved the manuscript. Views expressed in this paper are those of the authors and do not reflect official policy of the U.S. Environmental Protection Agency.

CONFLICT OF INTEREST STATEMENT

The authors have no conflicts of interest to declare.

DATA AVAILABILITY STATEMENT

All data and codes used for this analysis will be publicly available at data.gov.

ORCID

Lester L. Yuan https://orcid.org/0000-0002-9462-824X
Michael J. Paul https://orcid.org/0000-0002-2050-3663

REFERENCES

Alexander, R.B., E.W. Boyer, R.A. Smith, G.E. Schwarz, and R.B. Moore. 2007. "The Role of Headwater Streams in Downstream Water Quality." *Journal of the American Water Resources Association* 43: 41–59.

Banner, E.B.K., A.J. Stahl, and W.K. Dodds. 2009. "Stream Discharge and Riparian Land Use Influence In-Stream Concentrations and Loads of Phosphorus from Central Plains Watersheds." *Environmental Management* 44: 552–65.

Bernot, M.J., and W.K. Dodds. 2005. "Nitrogen Retention, Removal, and Saturation in Lotic Ecosystems." *Ecosystems* 8: 442–53.

Caraco, N.F., and J.J. Cole. 1999. "Human Impact on Nitrate Export: An Analysis Using Major World Rivers." *Ambio* 28: 167–70.

Dillon, P.J., and F.H. Rigler. 1974. "The Phosphorus-Chlorophyll Relationship in Lakes." *Limnology and Oceanography* 19: 767–73.

Dodds, W.K., V.H. Smith, and K. Lohman. 2002. "Nitrogen and Phosphorus Relationships to Benthic Algal Biomass in Temperate Streams." *Canadian Journal of Fisheries and Aquatic Sciences* 59: 865–74.

Fee, E.J. 1979. "A Relation between Lake Morphometry and Primary Productivity and Its Use in Interpreting Whole-Lake Eutrophication Experiments." *Limnology and Oceanography* 24: 401–16.

Filstrup, C.T., T. Wagner, P.A. Soranno, E.H. Stanley, C.A. Stow, K.E. Webster, and J.A. Downing. 2014. "Regional Variability among Nonlinear Chlorophyll—Phosphorus Relationships in Lakes." *Limnology and Oceanography* 59: 1691–703.

Griffiths, N.A., and L.T. Johnson. 2018. "Influence of Dual Nitrogen and Phosphorus Additions on Nutrient Uptake and Saturation Kinetics in a Forested Headwater Stream." *Freshwater Science* 37: 810–25.

Haggard, B.E., D.R. Smith, and K.R. Brye. 2007. "Variations in Stream Water and Sediment Phosphorus among Select Ozark Catchments." *Journal of Environmental Quality* 36: 1725–34.

Hall, R.O., Jr., M.A. Baker, E.J. Rosi-Marshall, J.L. Tank, and J.D. Newbold. 2013. "Solute-Specific Scaling of Inorganic Nitrogen and Phosphorus Uptake in Streams." *Biogeosciences* 10: 7323–31.

Hall, R.O., Jr., E.S. Bernhardt, and G.E. Likens. 2002. "Relating Nutrient Uptake with Transient Storage in Forested Mountain Streams." *Limnology and Oceanography* 47: 255–65.

Hall, R.O., Jr., B.J. Peterson, and J.L. Meyer. 1998. "Testing a Nitrogen-Cycling Model of a Forest Stream by Using a Nitrogen-15 Tracer Addition." *Ecosystems* 1: 283–98.

Heiskary, S.A., and R.W. Bouchard. 2015. "Development of Eutrophication Criteria for Minnesota Streams and Rivers Using Multiple Lines of Evidence." *Freshwater Science* 34: 574–92.

Howarth, R.W., G. Billen, D. Swaney, A. Townsend, N. Jaworski, K. Lajtha, J.A. Downing, et al. 1996. "Regional Nitrogen Budgets and Riverine N & P Fluxes for the Drainages to the North Atlantic Ocean: Natural and Human Influences." In *Nitrogen Cycling in the North Atlantic Ocean and Its Watersheds*, edited by R.W. Howarth, 75–139. Dordrecht, The Netherlands: Springer.

Johnes, P.J. 2007. “Uncertainties in Annual Riverine Phosphorus Load Estimation: Impact of Load Estimation Methodology, Sampling Frequency, Baseflow Index and Catchment Population Density.” *Journal of Hydrology* 332: 241–58.

Kunimatsu, T., M. Sudo, and T. Kawachi. 1999. “Loading Rates of Nutrients Discharging from a Golf Course and a Neighboring Forested Basin.” *Water Science and Technology* 39: 99–107.

Lewis, W.M., and W.A. Wurtsbaugh. 2008. “Control of Lacustrine Phytoplankton by Nutrients: Erosion of the Phosphorus Paradigm.” *International Review of Hydrobiology* 93: 446–65.

Lewis, W.M., W.A. Wurtsbaugh, and H.W. Paerl. 2011. “Rationale for Control of Anthropogenic Nitrogen and Phosphorus to Reduce Eutrophication of Inland Waters.” *Environmental Science & Technology* 45: 10300–05.

Lintern, A., L. McPhillips, B. Winfrey, J. Duncan, and C. Grady. 2020. “Best Management Practices for Diffuse Nutrient Pollution: Wicked Problems across Urban and Agricultural Watersheds.” *Environmental Science & Technology* 54: 9159–74.

Meyer, J.L. 1979. “The Role of Sediments and Bryophytes in Phosphorus Dynamics in a Headwater Stream Ecosystem.” *Limnology and Oceanography* 24: 365–75.

Meyer, J.L., and G.E. Likens. 1979. “Transport and Transformation of Phosphorus in a Forest Stream Ecosystem.” *Ecology* 60: 1255–69.

MNPCA. 2019. *Watershed Pollutant Load Monitoring Network Standard Operating Procedures and Guidance*. Saint Paul, MN: Minnesota Pollution Control Agency.

MNPCA. 2023a. *Standard Operating Procedures Intensive Watershed Monitoring—Stream Water Quality Sampling*. Saint Paul, MN: Minnesota Pollution Control Agency.

MNPCA. 2023b. *Standard Operating Procedures Intensive Watershed Monitoring—Lake Water Quality Sampling*. Saint Paul, MN: Minnesota Pollution Control Agency.

Mulholland, P.J., E.R. Marzolf, J.R. Webster, D.R. Hart, and S.P. Hendricks. 1997. “Evidence That Hyporheic Zones Increase Heterotrophic Metabolism and Phosphorus Uptake in Forest Streams.” *Limnology and Oceanography* 42: 443–51.

Mulholland, P.J., J.D. Newbold, J.W. Elwood, L.A. Ferren, and J.R. Webster. 1985. “Phosphorus Spiralling in a Woodland Stream: Seasonal Variations.” *Ecology* 66: 1012–23.

Newbold, J.D., J.W. Elwood, R.V. O'Neill, and A.L. Sheldon. 1983. “Phosphorus Dynamics in a Woodland Stream Ecosystem: A Study of Nutrient Spiralling.” *Ecology* 64: 1249–65.

Novak, J.M., K.C. Stone, D.W. Watts, and M.H. Johnson. 2003. “Dissolved Phosphorus Transport during Storm and Base Flow Conditions from an Agriculturally Intensive Southeastern Coastal Plain Watershed.” *Transactions of the American Society of Agricultural Engineers* 46: 1355.

Paerl, H.W., J.T. Scott, M.J. McCarthy, S.E. Newell, W.S. Gardner, K.E. Havens, D.K. Hoffman, S.W. Wilhelm, and W.A. Wurtsbaugh. 2016. “It Takes Two to Tango: When and Where Dual Nutrient (N & P) Reductions Are Needed to Protect Lakes and Downstream Ecosystems.” *Environmental Science & Technology* 50: 10805–13.

Payn, R.A., J.R. Webster, P.J. Mulholland, H.M. Valett, and W.K. Dodds. 2005. “Estimation of Stream Nutrient Uptake from Nutrient Addition Experiments.” *Limnology and Oceanography: Methods* 3: 174–82.

Quinlan, R., A. Filazzola, O. Mahdiyan, A. Shuvo, K. Blagrave, C. Ewins, L. Moslenko, D.K. Gray, C.M. O'Reilly, and S. Sharma. 2021. “Relationships of Total Phosphorus and Chlorophyll in Lakes Worldwide.” *Limnology and Oceanography* 66: 392–404.

Rast, W., R.A. Jones, and G.F. Lee. 1983. “Predictive Capability of U.S. OECD Phosphorus Loading-Eutrophication Response Models.” *Journal Water Pollution Control Federation* 55: 990–1003.

Smith, V.H. 1982. “The Nitrogen and Phosphorus Dependence of Algal Biomass in Lakes: An Empirical and Theoretical Analysis.” *Limnology and Oceanography* 27: 1101–12.

Soranno, P.A., S.R. Carpenter, and R.C. Lathrop. 1997. “Internal Phosphorus Loading in Lake Mendota: Response to External Loads and Weather.” *Canadian Journal of Fisheries and Aquatic Sciences* 54: 1883–93.

Stan Development Team. 2016. “Stan Modeling Language Users Guide and Reference Manual, Version 2.14.0.” http://mc-stan.org.

Tank, J.L., E.J. Rosi-Marshall, M.A. Baker, and R.O. Hall. 2008. “Are Rivers Just Big Streams? A Pulse Method to Quantify Nitrogen Demand in a Large River.” *Ecology* 89: 2935–45.

USEPA. 2010. *Using Stressor-Response Relationships to Derive Numeric Nutrient Criteria*. Washington, DC: Office of Water, U.S. Environmental Protection Agency.

USEPA. 2011. *2012 National Lakes Assessment*. Washington, DC: Field Operations Manual. Office of Water, US Environmental Protection Agency.

USEPA. 2012. *2012 National Lakes Assessment*. Washington, DC: Laboratory Operations Manual. U.S. Environmental Protection Agency.

USEPA. 2013. *National Rivers and Streams Assessment 2013–2014: Field Operations Manual—Wadeable*. Washington DC: Office of Water.

USEPA. 2022. *National Lakes Assessment 2017: Technical Support Document*. Washington DC: Office of Water and Office of Research and Development, U.S. Environmental Protection Agency.

Valett, H.M., J.A. Morrice, C.N. Dahm, and M.E. Campana. 1996. “Parent Lithology, Surface–Groundwater Exchange, and Nitrate Retention in Headwater Streams.” *Limnology and Oceanography* 41: 333–45.

Vollenweider, R.A., and J. Kerekes. 1982. *Eutrophication of Waters*. Paris: Monitoring Assessment and Control. Organization for Economic Co-Operation and Development (OECD).

Wagner, T., N.R. Lottig, M.L. Bartley, E.M. Hanks, E.M. Schliep, N.B. Wikle, K.B.S. King, et al. 2020. “Increasing Accuracy of Lake Nutrient Predictions in Thousands of Lakes by Leveraging Water Clarity Data.” *Limnology and Oceanography Letters* 5: 228–35.

Webster, J.R., P.J. Mulholland, J.L. Tank, H.M. Valett, W.K. Dodds, B.J. Peterson, W.B. Bowden, et al. 2003. “Factors Affecting Ammonium Uptake in Streams—An Inter-Biome Perspective.” *Freshwater Biology* 48: 1329–52.

Wellen, C., G.B. Arhonditsis, T. Labencki, and D. Boyd. 2014. “Application of the SPARROW Model in Watersheds with Limited Information: A Bayesian Assessment of the Model Uncertainty and the Value of Additional Monitoring.” *Hydrological Processes* 28: 1260–83.

Yuan, L.L. 2022. “Improving Estimates of Phosphorus Loads Using Hierarchical Models.” *Journal of Hydrology* 614: 128558.

How to cite this article: Yuan, Lester L. and Michael J. Paul 2024. “Predicting Lake Chlorophyll From Stream Phosphorus Concentrations.” *JAWRA Journal of the American Water Resources Association* 00(0): 1–8. https://doi.org/10.1111/1752-1688.13243.