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Granular measures of agricultural land use influence lake nitrogen and phosphorus differently at macroscales

Joseph Stachelek [1,8], W. Weng,[2] C. C. Carey [3], A. R. Kemanian [4], K. M. Cobourn,[5] T. Wagner [6], K. C. Weathers [7], and P. A. Soranno [1]

[1]*Department of Fisheries and Wildlife, Michigan State University, 480 Wilson Road, East Lansing, Michigan 48824 USA*
[2]*School of Business, State University of New York College at Geneseo, 1 College Circle, Geneseo, New York 14454 USA*
[3]*Department of Biological Sciences, Virginia Tech, 926 W Campus Drive, Blacksburg, Virginia 24061 USA*
[4]*Department of Plant Science, The Pennsylvania State University, 247 Agricultural Sciences and Industries Bldg., University Park, Pennsylvania 16802 USA*
[5]*Department of Forest Resources and Environmental Conservation, Virginia Tech, 310 W Campus Drive, Blacksburg, Virginia 24061 USA*
[6]*U.S. Geological Survey, Pennsylvania Cooperative Fish and Wildlife Research Unit, The Pennsylvania State University, University Park, Pennsylvania USA*
[7]*Cary Institute of Ecosystem Studies, 2801 Sharon Turnpike, Millbrook, New York 12545 USA*

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Abstract. Agricultural land use is typically associated with high stream nutrient concentrations and increased nutrient loading to lakes. For lakes, evidence for these associations mostly comes from studies on individual lakes or watersheds that relate concentrations of nitrogen (N) or phosphorus (P) to aggregate measures of agricultural land use, such as the proportion of land used for agriculture in a lake's watershed. However, at macroscales (i.e., in hundreds to thousands of lakes across large spatial extents), there is high variability around such relationships and it is unclear whether considering more granular (or detailed) agricultural data, such as fertilizer application, planting of specific crops, or the extent of near-stream cropping, would improve prediction and inform understanding of lake nutrient drivers. Furthermore, it is unclear whether lake N and P would have different relationships to such measures and whether these relationships would vary by region, since regional variation has been observed in prior studies using aggregate measures of agriculture. To address these knowledge gaps, we examined relationships between granular measures of agricultural activity and lake total phosphorus (TP) and total nitrogen (TN) concentrations in 928 lakes and their watersheds in the Northeastern and Midwest U.S. using a Bayesian hierarchical modeling approach. We found that both lake TN and TP concentrations were related to these measures of agriculture, especially near-stream agriculture. The relationships between measures of agriculture and lake TN concentrations were more regionally variable than those for TP. Conversely, TP concentrations were more strongly related to lake-specific measures like depth and watershed hydrology relative to TN. Our finding that lake TN and TP concentrations have different relationships with granular measures of agricultural activity has implications for the design of effective and efficient policy approaches to maintain and improve water quality.

Key words: *agriculture; fertilizer; lakes; manure; nitrogen; phosphorus; water quality.*

Introduction

Freshwaters are vulnerable to eutrophication in areas of high agricultural land use and land cover because agricultural activities are associated with high nutrient runoff and loading to groundwater and streams (Arbuckle and Downing 2001, Allan 2004, Taranu and Gregory-Eaves 2008 , Daniel et al. 2010). High runoff and loading in these areas is a result of high rates of nutrient input combined with hydrologic modifications that decrease the travel time of these inputs from the land surface to lakes (Blann et al. 2009). Surprisingly, while some studies have found strong relationships between agricultural land use and land cover (hereafter referred to as "land use" or LULC) and lake nutrient concentrations (Arbuckle and Downing 2001, Taranu and Gregory-Eaves 2008), others have found more mixed results (Jones et al. 2008), particularly in studies that include many lakes located in multiple regions (Soranno et al. 2015). Further examples of such macroscale studies (see Heffernan et al. 2014) in which lakes are spread across many regions at distances spanning hundreds to thousands of kilometers include Collins et al.

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[8]E-mail: stachel2@msu.edu

(2017) and Read et al. (2015), who found that the strength of agriculture and lake nutrient relationships varied depending on geographic region and lake characteristics.

Mixed results from prior studies may be due to two difficulties in quantifying lake nutrient and agricultural land use relationships. First, the pathways of nutrients from fields to streams and ultimately to lakes are complex and indirect (Heathwaite et al. 2003, King et al. 2005, Cherry et al. 2008). For example, in order for nitrogen applied as fertilizer to reach a lake, it must be transported to streams or groundwater in excess of microbial denitrification, plant use, and microbial uptake. Then, it must travel, again, often undergoing repeated chemical transformation as it passes through riparian buffers and along stream networks before finally entering the lake (Maranger et al. 2018). Each step of the journey represents an opportunity for those nutrients to be sequestered or removed. Further, overall hydrologic transport is influenced by soil type (Naiman et al. 2010) and topography. Thus, the nutrients that ultimately enter a lake are a function of filtering by the landscape as well as geochemical transformation processes that are difficult to capture at broad scales (Canham et al. 2012, Maranger et al. 2018).

Second, much of our evidence for a connection between agricultural land use and increased nutrient concentrations comes from studies focusing on a single watershed or on several watersheds within a single geographic region (Renwick et al. 2008, Daniel et al. 2010, Hayes et al. 2015, Capel et al. 2018*a*). These studies tend to focus on very detailed measures of agricultural activity such as tillage and other practices, nutrient amendments, and their spatial arrangement. However, studies at broader spatial scales (i.e., the macroscale; Heffernan et al. 2014), which aim to provide a more general view of relationships between lake nutrient concentrations and agriculture, tend to focus only on relatively coarse measures of agricultural activity (Read et al. 2015, Fergus et al. 2017, Filstrup et al. 2018, Schmadel et al. 2019). As a result, it is unclear to what extent the mixed results from prior broad-scale studies might be due to the limited use of detailed measures of agricultural activity or simply from regional variation.

There are two ways in which detailed (i.e., granular) measures of agricultural activity may be substituted for their coarse (i.e., aggregate) counterparts. The first is by using granular measures that are recorded in the same locations as their aggregate equivalents but are more descriptive. For example, in broad-scale studies, the proportion of land used for agriculture in a lake watershed is sometimes replaced by separate representations of the land used for pasture and the land used for row-crops (Abell et al. 2011, Collins et al. 2017). The second is by using granular measures that have the same description as their aggregate equivalents, but that are measured in more specific locations. For example, a small number of lake studies have compared the proportion of land used for agriculture in near-stream buffers vs. the watershed as a whole (Gémesi et al. 2011, Soranno et al. 2015). Although the term granular can be used in a general sense to describe any detailed agricultural measure, we define the term more narrowly as only those that have a specific aggregate counterpart (Table 1).

Prior use of granular data in broad-scale studies of lake water quality has been limited. For this reason, findings from broad-scale studies may be less useful in applied management settings because coarse (i.e., aggregate) land-use and land-cover change metrics have become less widely used policy instruments (Morefield et al. 2016). Instead, recent policy interventions go beyond aggregate measures of agricultural activity to target more specific measures such as implementation of specific farming practices, no-till agriculture, and construction of riparian buffer strips (Yang et al. 2005, NRC 2010, Capel et al. 2018*b*). Thus, broad-scale studies could be made more relevant for informing policy interventions if they used covariates that have a similar level of granularity to those used in fine-scale studies. For example, implementation of no-till agriculture policies may be better informed by covariates at the granular crop level rather than solely by aggregate covariates like land used for agriculture (Appendix S1: Fig. S1).

Table 1. Medians followed by first (Q25) and third (Q75) quantiles of predictor variables for 928 lakes.

Granularity and variable	Median	Q25	Q75
Aggregate			
Agriculture (%)	42	25	63
Granular			
Pasture (%)	14	7	24
Corn (%)	7	2	17
Soybeans	4	1	14
Buffer agriculture	25	11	48
Buffer natural	41	23	59
Fertilizer N	55	32	91
Fertilizer P	10	6	16
Manure N	27	17	45
Manure P	7	5	12
Other			
Forest	25	12	46
Wetlands	3	1	8
N deposition	6	5	7
Precipitation	910	830	1000
Baseflow	49	33	62
Wetland potential	15	5	26
Soil organic carbon	4000	2900	5300
Clay	10	5	17
Maximum depth	9	6	14
Watershed-lake ratio	15	6	34

Notes: Also shown is whether each predictor is defined as an aggregate or granular measure of agriculture or as a non-agriculture (other) predictor. Dashed entries for the granularity category indicate an identical categorization as the preceding predictor.

One likely reason that broad-scale studies have rarely used granular agricultural data is that until recently, such data have not been available with corresponding lake nutrient concentration data over large geographic extents. Although a few examples exist of studies connecting granular agricultural data to either stream nitrogen or phosphorus concentrations at the macroscale (Boyer et al. 2002, Metson et al. 2017, Bellmore et al. 2018), most studies have focused on either nitrogen (N) or phosphorus (P) but not on both at the same time (Alexander et al. 2008). Crucially, we are not aware of prior work examining relationships between a multiple granular measures of agricultural activity on either lake N or P concentrations at macroscales.

There are several plausible expectations, which are based on the findings of broad-scale stream studies as well as the findings of fine-scale lake studies, for the type of relationships between such measures and lake nutrient concentrations that may emerge at macroscales. First, we expect that increased nutrient inputs to the land surface as fertilizer and manure will increase lake nutrient concentrations (Renwick et al. 2008, Bellmore et al. 2018). Second, we expect that lakes with watersheds that have high soil clay content and high soil organic carbon content will have higher lake nutrient concentrations. This will occur because clay soils tend to have higher rates of surface runoff and have higher organic matter content relative to sandy soils, despite the tendency for higher organic matter content to increase water storage and reduce surface runoff (Capel et al. 2018*a*). Finally, we expect that lakes with stream networks characterized by extensive near-stream agriculture will have higher nutrient concentrations because there will be less interception of agricultural runoff (Naiman et al. 2010).

Although we can formulate potential expectations for relationships between agricultural activities and lake nutrients at the macroscale by building on the findings of prior studies, several key uncertainties remain. The first key uncertainty is the extent to which lake and watershed characteristics, such as watershed hydrology and soil type, affect relationships between granular measures of agricultural activity and lake nutrient concentrations at the macroscale. For example, macroscale studies have found that lake P concentrations are strongly dependent on lake depth (Collins et al. 2017), but the degree to which granular agricultural data provide additional explanatory power is unknown. Similarly, Abell et al. (2011) found that watershed to lake area ratio (i.e., lake water residence time) was positively related to lake N concentrations after controlling for aggregate measures of agricultural land use, but it is unknown whether this mediation effect would also affect relationships with more granular measures of agriculture.

The second key uncertainty is the extent to which relationships between granular measures of agricultural activity and lake nutrient concentrations vary regionally. For example, previous macroscale studies on lake nutrient concentrations have found that relationships between lake chlorophyll and nutrient concentrations vary regionally according to hydrologic subregions (Wagner et al. 2011, Qian et al. 2019). Models in which separate relationships (e.g., slopes) are estimated for different regions, such as those used by Wagner et al. (2011), can be used to test differences among regions in the sensitivity to nutrient predictors. Wagner et al. (2011) found that the slope of the chlorophyll to P relationship was notably higher in several of their study regions and found that lakes with high pasture land use in their watershed were more sensitive to changes in P concentrations (larger, positive slope estimate). They suggest that elevated sensitivity in high pasture regions is due to dual N and P nutrient enrichment associated with this land cover type. Given the findings of this and other studies in stream ecosystems (Alexander et al. 2008), it follows that other relationships in lakes may vary regionally, but whether or not this includes relationships with granular measures of agricultural activity remains unknown.

We addressed the knowledge gaps described above by asking two questions using data from approximately 900 lakes in the northeastern and midwestern United States: (1) How do granular measures of agricultural activity relate to lake N and P concentrations? And (2) how do relationships between agricultural activities and lake nutrients vary regionally among hydrologic and climatic regions? To answer these questions, we fit statistical models of lake nutrient concentrations as a function of granular measures of agricultural activity such as the proportion of watershed area land use of specific crops, and near-stream land use, as well as fertilizer and manure applications. We also included a variety of lake and watershed characteristics as predictors to account for the influence of other drivers. Finally, our models included a hierarchical component where relationships between watershed land use and lake nutrient concentrations were allowed to vary among hydrologic subregions to examine potential regional variation in these relationships.

Methods

Data description

We analyzed data on lake total nitrogen (TN) and total phosphorus (TP) concentrations from the LAGOS-NE data product (Soranno and Cheruvelil 2017*a*). The LAGOS-NE nutrient data are limited to surface (or epilimnetic) samples and were derived from federal, state, tribal, and non-profit agencies, as well as university researchers and citizen scientist data collections (Soranno et al. 2017). We collapsed lake nutrient data to long-term median values computed using all data from the summer stratified period (i.e., 15 June–15 September) available for each lake between 2000 and 2010. For the lakes that met our selection criteria (see below) the median number of samples per lake was nine

(range = 3–94) and the median number of years sampled was four (range = 2–10).

Our first source for granular agricultural information was the 2010 Cropland Data Layer (CDL; USDA 2019), which we used to generate lake watershed and stream buffer estimates of the proportion of land cover due to specific crops such as corn and soybeans. We used the R package cdlTools to access CDL products (Chen 2018). We used the 2010 CDL data because this was the first year of high resolution (30 × 30 m) CDL data collection that matched our lake nutrient data collection window. Because the CDL contains detailed coverage for dozens of crops, including rare crops with little to no coverage, we recategorized CDL data based on Lark et al. (2015) to a more limited set of categories (Appendix S1: Table S1).

As a more granular representation of watershed agricultural land use, we measured the proportion of land cover in agricultural and "natural" land uses in 100-m buffers of lake shorelines and streams for each lake watershed. We chose a 100-m buffer width because this width is inclusive of nearly all riparian buffers (Mayer et al. 2007). Here agricultural land use is defined in the aggregate sense as the proportion of land used for agriculture in a lake's watershed whereas "natural" land uses include the sum of all non-agriculture and non-developed CDL classes. We identified the streams associated with each lake using the stream network extraction tool in the nhdR interface (Stachelek 2019*a*,*b*) to the National Hydrography Network (USGS 2019). We compiled soil characteristics for each lake watershed using the Gridded Soil Survey Geographic Database (gSSURGO; USDA 2019) where we used the python package gssurgo (Stachelek 2019*a*,*b*) to access gSSURGO products. One such product was wetland potential, defined as the percentage of the soil grid that meets the criteria for hydric soils formed under conditions of saturation, flooding, or ponding long enough to develop anaerobic conditions but not so long as to be classified as a permanent waterbody (USDA 2019). Finally, we compiled mean annual nutrient inputs via fertilizer and manure to lake watersheds from 1982 to 2001 using county level data provided by Ruddy et al. (2006). We spatially aligned these county level estimates to lake watershed polygons provided by LAGOS-NE (Soranno and Cheruvelil 2017*b*) using the area-weighted interpolation functions provided by the sf R package (Pebesma 2018). All of our data and data processing code are available online (see Data Availability).

Location information

We restricted the lakes included in the study to those located within the footprint of LAGOS-NE which includes lakes located in 17 northeastern and midwest U.S. states (Soranno et al. 2017). We excluded lakes from our analysis if they had a surface area >400 km^2 or a maximum depth >35 m. These removals resulted in exclusion of ~40 lakes which we regarded as outliers that would likely have undue influence on model results because such large and deep lakes are likely to respond differently to enrichment as a result of enhanced stratification. To ensure an adequate comparison between aggregate and granular measures of agriculture, we further limited lakes in our study to those with at least 10% of the total watershed area devoted to agricultural land use and those that were sampled at least three times between 2000 and 2010. A total of 928 lakes met these selection criteria (Fig. 1). Because we focused on lakes in agricultural watersheds, more than 35% of lakes in our study are considered eutrophic to hypereutrophic using chlorophyll *a* as a diagnostic vs. only 15% for all lakes from Soranno et al. (2017) located within our study extent (Appendix S1: Fig. S3). For the regional terms in our models, we used hydrologic regions at the sub-basin (i.e., HUC4) level because this level was small enough to give a sense of overall spatial variation but large enough to encompass sufficient numbers of lakes to estimate within region variance.

Model overview

We evaluated the effects of agricultural activities on lake TN and TP concentrations using a Bayesian hierarchical modeling approach. A list of lake and watershed covariates with their summary statistics is available in Table 1. In the first part of our model evaluation, we compared models that each had only a single measure of watershed land use along with all remaining non-watershed land-use predictors. These non-watershed land-use predictors were included in every fitted model and were defined as measures of near-stream land use, soil characteristics, and lake and watershed characteristics. We took this approach of evaluating one watershed land-use measure at a time for two reasons: (1) because measures of watershed land use were highly correlated and (2) because it allowed us to more rigorously test our expectation that granular measures of agriculture provide additional explanatory power beyond that offered by more typical aggregate measures of agriculture.

In the second part of our model evaluation, we selected the top-ranked watershed land-use model according to our selection criteria for lake N and P for further inspection of their standardized coefficient values (See Table 1). Our models were of the form:

$$y_i \sim N\left(\alpha_{j(i)} + \beta_1 \times X_{1i} \ldots \beta_n \times X_{ni} + \gamma_{1j(i)} \times W_{1i} + \gamma_{mj(i)} \times W_{mi}\right)$$

$$\begin{pmatrix} \alpha_j \\ \gamma_{1j} \end{pmatrix} \sim \mathrm{MVN}\left(\begin{pmatrix} \mu_\alpha \\ \mu_{\gamma 1} \end{pmatrix}, \Sigma\right)$$

where y_i is either TN or TP concentration for lake i, and β are "global" (i.e., fixed effect) coefficients. This set of global coefficients included estimates for watershed soil characteristics, near-stream land use, as well as fertilizer

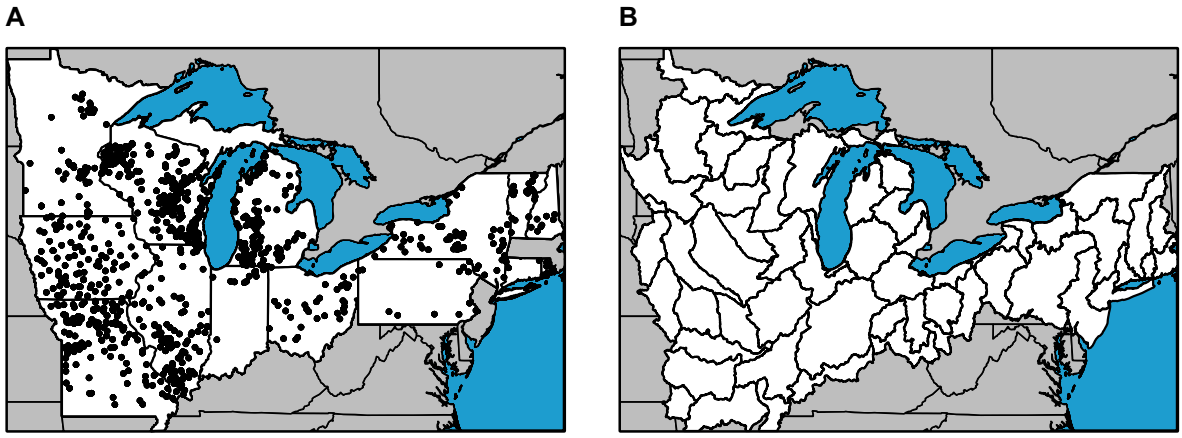

FIG. 1. (A) Map of lake locations and (B) hydrologic (HUC4) regions.

and manure inputs for each lake (X_i). Whereas β coefficients were estimated as fixed effects, γ coefficients and α intercepts were estimated as varying (i.e., random) slopes and intercepts respectively among m hydrologic regions j on watershed land-use (W_{ij}). Region-specific intercepts α and γ slopes were assumed to come from a multivariate normal distribution (MVN) where μ_α and $\mu_{\gamma 1}$ are their respective grand mean (i.e., population level) estimates. We tested a variety of watershed land-use types for W_{ij}, including both granular and more aggregate measures of agricultural activity. Our only aggregate measure of agricultural activity was agricultural land use whereas we used several granular measures of agricultural activity. These included both detailed measures of watershed land use such as corn and soybean cover as well as more detailed measures of nutrient inputs and near-stream land use (Table 1). We included measures of both N and P inputs in both N and P models because of the possibility for stoichiometric interaction. Given our regularization scheme (i.e., our use of "horseshoe priors" described below) there was little reason to exclude P inputs from N models (and vice versa) because unless P inputs are strongly related to lake TN concentration, their coefficient will be forced close to zero.

All models had the same set of fixed effect coefficients while each individual model used a single different watershed land-use variable as a random effect. This modeling strategy is supported by our view that watershed land use is an indirect proxy (sensu King et al. 2005, Burcher et al. 2007, Hayes et al. 2015) for other unquantifiable agricultural activities. Therefore, we expect the makeup of specific activities represented by this indirect measure to vary regionally. This contrasts with other predictor variables like lake depth, where we have little evidence from prior studies that its effect on lake nutrient concentrations is spatially variable.

Prior to model fitting, we examined the bivariate relationships between lake nutrient concentrations and all predictor variables using Pearson's correlation coefficients (Appendix S1: Fig. S5) to determine the overall structure of the predictor dataset. We did not use the results of this exercise for building our model, performing model selection, or variable selection. For qualitative analysis of our model results, we classified predictor variables following Collins et al. (2017) into categories based on the dominant mechanism affecting lake nutrient concentrations, which includes nutrient inputs, nutrient transport, spatial configuration of land use in stream buffers (spatial configuration), lake characteristics, and watershed land use (LULC).

We fit all models in a Bayesian framework using the brms R package interface to the Stan statistical program (Bürkner 2017, Stan Development Team 2017). We used horseshoe shrinkage priors on all fixed-effect coefficients to evaluate variable importance (Carvalho et al. 2010). We considered a response variable sensitive to a given predictor if the predictor's 95% credible interval did not overlap 0. We standardized all predictor variables by subtracting the mean of each variable and dividing by their respective standard deviation so that model coefficients could be compared on roughly the same scale. As a result, the relative sensitivity of a response variable to a particular predictor is related to the relative magnitude of its coefficient estimate.

We evaluated model fit of each watershed land-use variable (i.e., each model having one regionally varying coefficient) in two ways. First, we computed a Bayesian R^2 following the method of Gelman et al. (2017) and second, we computed differences in expected log predictive density (ELPD) using the leave-one-out cross-validation routines provided by the loo R package and implemented in brms (Vehtari et al. 2017). The loo package uses leave-one-out cross-validation to estimate overall model error by computing the average error of models iteratively trained on all the data except for a single point. ELPD values have a similar interpretation to information criterion measures such as Akaike information criterion (AIC) or Watanabe-Akaike information criterion (WAIC) except that values are on a different scale (Gelman et al. 2013). Typically, models are

considered to be different if they are separated by an AIC value of >2 (Anderson and Burnham 2002), which is equivalent to an ELPD value of −1 (Gelman et al. 2013). We report differences in ELPD among models using the notation ΔELPD. We selected the model with the lowest absolute value ELPD as the top-ranked model for detailed reporting and discussion as this signifies the model with the lowest leave-one-out cross-validation error for N and P, respectively.

We used the default settings of brms to generate posterior estimates using four chains of 4,000 iterations each with no thinning and discarding the first 1,000 iterations. We examined model fits to ensure that all models had acceptable convergence of MCMC chains and had approximately normal model residuals. We further tested for spatial correlation among model residuals using the spind R package (Carl et al. 2018). All of our code for model fitting and evaluation is available online (see Data Availability).

Results

Effects of agriculture on lake nitrogen and phosphorus

Lake characteristics (e.g., maximum depth and watershed to lake area ratio) along with measures of nutrient transport (e.g., baseflow) and near-stream agriculture were significant predictors in all lake N and P models that we fit. When we compared among different models for each nutrient individually, we found that those with agricultural watershed land use (in the aggregate sense) were top ranked (i.e., had the lowest absolute value leave-one-out cross-validation score) for models of both TN and TP concentrations (Fig. 2, Table 2). Although we observed no difference in the specific watershed land-use predictor used in each top-ranked model, we found differences in the extent to which each top-ranked model was substantially different from lower ranked models. For example, in the case of P, all models had nearly identical R^2 (0.63) and the difference between the top-ranked model and second-ranked model was modest (ΔELPD = 0.41). For N models, however, agricultural and corn land-use models had higher R^2 (0.58) compared to other models and the difference between the top-ranked and second-ranked model was more substantial (ΔELPD = 2.58, Fig. 2, Table 1).

When we looked more closely at each top-ranked model, we found similarities in the types of predictors that contributed significantly to the top-ranked N and P models (Fig. 3). First, both N and P models included measures of lake characteristics such as maximum depth and watershed to lake area ratio as significant predictors, with the sign of these associated coefficients matching our conventional understanding, in which shallower lakes and lakes with greater hydrologic loads have higher TN and TP concentrations. Second, both models included measures of nutrient transport such as baseflow and precipitation, in which lakes with a "flashier" hydrology (i.e., having lower baseflow) where incoming water is primarily from surface runoff rather than from groundwater, had higher TN and TP concentrations. Finally, both models indicated that high near-stream agriculture (i.e., a high proportion of the area adjacent to the stream network was in agricultural land use) was associated with lakes having higher TN and TP concentrations. Where N and P models differed was in the effect of soil clay content, in which soils with low clay content were associated with high lake N but had no significant relationship with P.

Although top-ranked N and P models shared some similarities in the type of predictors that contributed significantly to each model, the coefficients of these models differed in magnitude, and thus the top-ranked models varied in their sensitivity to specific predictors (Fig. 3). For example, the top-ranked P model was more sensitive to lake characteristics, whereas the top-ranked N model was more sensitive to watershed land use. Quantitatively, lake TP concentrations were more sensitive to maximum depth (β_{depth}: median = −0.39, SD = 0.04) compared to lake TN concentrations (β_{depth}: median = −0.14, SD = 0.04); whereas lake TN concentrations were more sensitive to watershed agriculture land use (β_{ag}: median = 0.44, SD = 0.11) compared to lake TP concentrations (β_{ag}: median = 0.10, SD = 0.08). Finally, although we found that near-stream agriculture was associated with both higher TN and TP concentrations (i.e., a source effect of near-stream agriculture), there was not a significant difference in the magnitude (i.e., sensitivity) of this coefficient between N ($\beta_{bufferag}$: median = 0.16, SD = 0.06) and P ($\beta_{bufferag}$: median = 0.12, SD = 0.06) models.

No predictors in the nutrient input category appeared to be strongly related to either TN or TP concentrations. One explanation may be that these variables covaried with watershed and near-stream land-use variables (Appendix S1: Fig. S5). In an attempt to further investigate this possibility, we fit alternative models excluding all land-use predictors. The results show that, at least in the case of N, removing these predictors caused model variance to be apportioned from watershed and buffer land-use predictors to N input and P fertilizer predictors (Appendix S1: Fig. S4). However, this non-land-use N model had a relatively poor fit (R^2 = 0.40) compared to the top-ranked model that included land use as a predictor (R^2 = 0.58).

Regional variation in agriculture sensitivity

Both TN and TP concentrations were sensitive to measures of watershed land use as well as near-stream agriculture (Fig. 2, Table 1). Despite these similarities, we found differences in both the magnitude of these effects and the extent to which we observed regional variation in watershed land-use sensitivity for N and P models (Fig. 4). For P, there was little evidence that sensitivity to watershed land use was regionally variable. More specifically, the credible intervals for the slope of each individual region overlapped the global slope estimate (Fig. 4). In contrast,

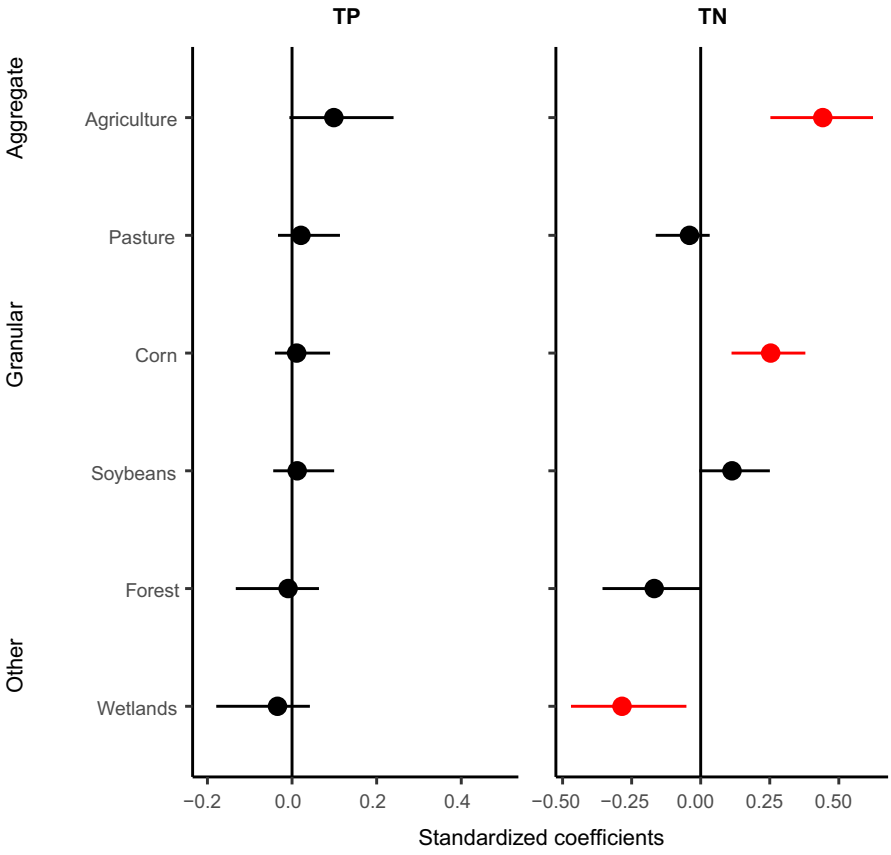

FIG. 2. Population-level slope estimates (μ_γ) for the effect of watershed land-use cover on lake total nitrogen (TN) and total phosphorus (TP) from six candidate models. Values shown are posterior medians (filled circles) and 95% credible intervals (solid lines). Also shown is a comparison to a zero effect (solid vertical line). Values that do not overlap zero are shaded in red. Coefficient estimates are reported relative to standardized predictor variables centered at zero with unit variance.

TABLE 2. Diagnostics for each model listed by regionally varying coefficient

Response	Term	R^2	LOO-ELPD
TP	agriculture	0.63	0.0
TP	wetlands	0.63	−0.41
TP	corn	0.63	−0.59
TP	pasture	0.63	−0.75
TP	forest	0.63	−0.76
TP	soybeans	0.63	−1.43
TN	agriculture	0.58	0.0
TN	corn	0.58	−2.58
TN	wetlands	0.54	−16.41
TN	soybeans	0.53	−20.88
TN	pasture	0.53	−21.01
TN	forest	0.53	−22.37

Notes: Table is sorted by decreasing R^2 and leave-one-out cross-validation (LOO) estimate of expected log predictive density (ELPD). ELPD has a similar interpretation to information criterion measures like AIC. Typically models are considered to be different if they are separated by an Akaike information criterion (AIC) value of >2, which is equivalent to an ELPD value of −1. TN, total N; TP, total P.

for N, we found evidence for regional variation in sensitivity to watershed land use. For this nutrient, the credible intervals for 2 of the 37 regions did not overlap the global estimate (Fig. 4). These regions were found in parts of Iowa, Minnesota, and Illinois and appear to be more sensitive to watershed land use, i.e., lake N increases at a faster rate per unit increase in agricultural land use compared to other regions (Fig. 5). The median soil clay content of watersheds in these regions was higher than the median across watersheds in all other regions (Fig. 6). Furthermore, these two regions had a unique combination of both high soil clay content and extensive tile drainage (Appendix S1: Fig. S6).

DISCUSSION

Effects of granular measures of agriculture on lake nitrogen and phosphorus

There is substantial unexplained variation around simple linear relationships between aggregate

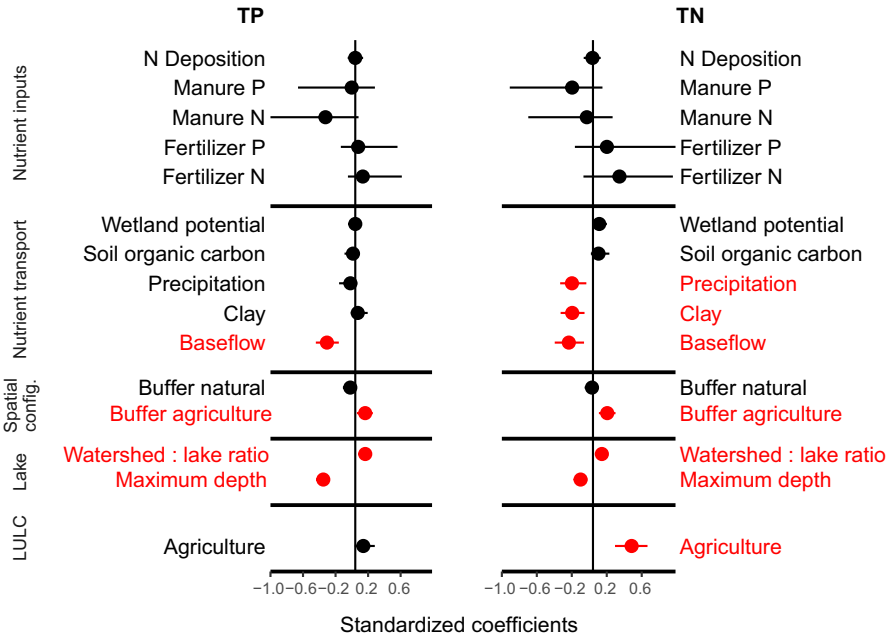

FIG. 3. Global (fixed effect) coefficient values (β, for all non-LULC [land use and land cover] predictors) and population level estimates for the effect of watershed land use (μ_γ, for LULC) on lake TN and TP for each respective top-ranked model. Note that the values for LULC here are identical to their corresponding values in Fig. 2. Values shown are posterior medians (solid circles) and 95% credible intervals (solid lines). Also shown is a comparison to a zero effect (solid vertical line). Values that do not overlap zero are shaded in red. Horizontal bars separate coefficients in distinct predictor categories. Coefficient estimates are reported relative to standardized predictor variables centered at zero with unit variance and correspond with β (and μ_γ for LULC) from Eq. 1. Config., configuration.

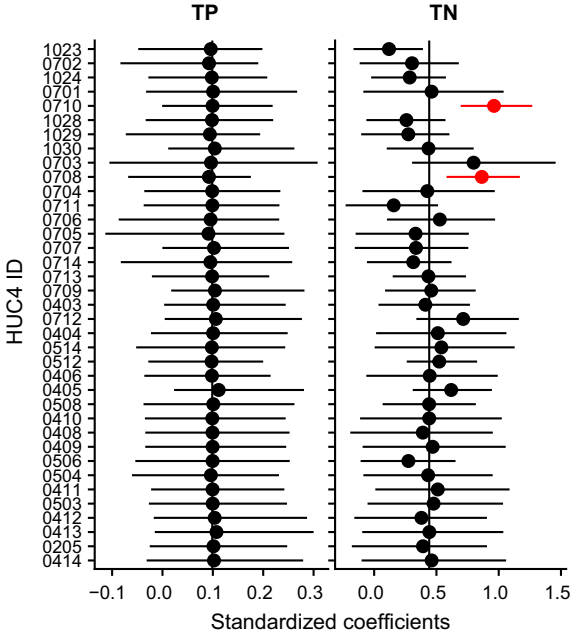

FIG. 4. Effect of watershed land use (γ_j) for individual regions in the top-ranked lake N and P models. Values shown are posterior medians (solid circles) and 95% credible intervals (solid lines) for individual hydrologic units (HUC4s) ordered from top to bottom according to longitude (west to east). Also shown is a comparison to a zero effect (solid vertical line). Values that are different from the population level effect are shaded in red.

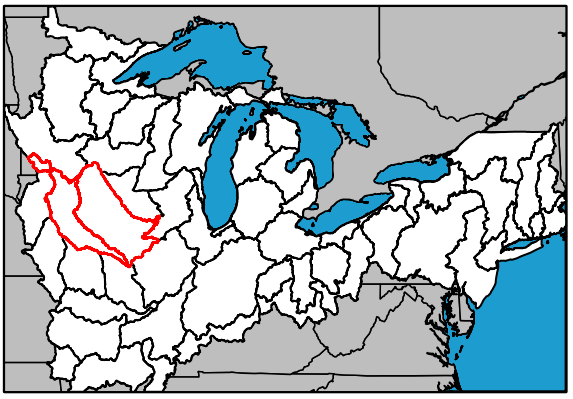

FIG. 5. Location of hydrologic regions sensitive to watershed land-use cover corresponding to highlighted credible intervals in Fig. 4.

representations of watershed land use in agriculture and both lake N and P (Appendix S1: Fig. S2). Our study was designed to examine these relationships in greater detail by testing whether more granular measures of agriculture could help explain some of this uncertainty for both N and P, and whether there were regional differences in these relationships. In sum, all models for TN and TP concentrations included at least one granular measure of agriculture, but there were also important differences between N and P related to the type of measures that were important to each. For example, we

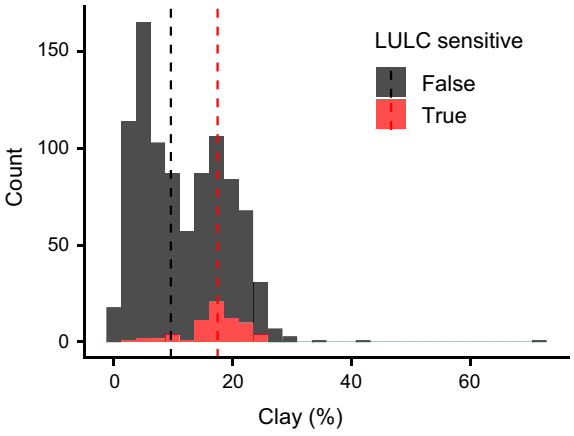

FIG. 6. Histograms showing the distribution of soil clay content for watersheds in regions sensitive to watershed land use (see highlighted credible intervals in Fig. 4) relative to watersheds all other regions. Medians for each group are shown as vertical dashed lines.

found little benefit of increased granularity of description (i.e., where measures are recorded in all the same locations as their aggregate equivalents) but consistent benefit of granular representation of the spatial configuration of land use in near-stream buffers.

Spatial configuration

The result showing that lake TN and TP concentrations are sensitive to the spatial configuration of land use in near-stream buffers is consistent with our expectation and prior research. Specifically, our finding that model coefficients on near-stream agriculture (i.e., agricultural land use in stream buffers) in all N and P models were significant and positive indicates a nutrient-delivery effect of stream buffer agriculture and suggests that the spatial configuration of agriculture with respect to stream buffers has a detectable influence on both lake N and P at macroscales. This is consistent with prior studies conducted over more limited spatial extents which examined relationships between lake or stream nutrient concentrations and agricultural land use in stream buffers (Baker et al. 2006, Diebel et al. 2009, Gémesi et al. 2011, Soranno et al. 2015). In contrast to near-stream agriculture, we found that near-stream "natural" land use was not significant in either N or P models. While we cannot definitively answer why, it may be related to the role that natural buffers play in nutrient cycling for N and P (Alexander et al. 2008, Canham et al. 2012). In the case of N, natural buffers may reduce stream loading by facilitating denitrification, whereas, in the case of P, natural buffers may trap particulate bound material without necessarily removing it (Mayer et al. 2007, Naiman et al. 2010). An alternative possibility is that we are observing a scale effect whereby the delivery effect of near-stream agriculture is spatially consistent whereas the trapping and removal effects of N and P by natural buffers is more spatially variable (Pärn et al. 2012). Finally, we may not have observed a protective effect of natural buffers because natural land use in buffers is too coarse of a proxy for "riparian buffers" composed of forest or herbaceous vegetation (Mayer et al. 2007).

Crop type

We found that for N models, land use of specific crops was significant, although it was not found in the top-ranked model. Specifically, we found that watershed land use in corn production was a significant predictor in the second-ranked N model (Table 2). In the case of P by contrast, neither aggregate nor granular measures of watershed land use were significant in any models (Fig. 2). This can be explained by our finding that all watershed land-use metrics had weak relationships with lake P, especially relative to the strong relationships we observed between P and other factors like lake depth, hydrology, and near-stream agricultural land use. Here, our finding is consistent with prior studies in stream ecosystems showing that the influence of hydrology exceeds that of agricultural land use or anthropogenic P inputs (Metson et al. 2017).

Nutrient inputs

None of the nutrient input variables were significant for either N or P models. On the surface, this would seem to contradict the findings of prior research such as that of Bellmore et al. (2018), who found that stream TN concentrations were more strongly controlled by N input predictors relative to measures of either watershed or near-stream land use. However, our finding has several alternative explanations. First, differences between our lake study and the Bellmore et al. (2018) stream study may simply point to differences in the controls on stream nitrogen concentrations relative to lake nitrogen concentrations (Allan 2004, Canham et al. 2012). Second, our finding that N and P were insensitive to nutrient input variables may be a result of shared variance between nutrient input variables and watershed land use. This makes sense given that agricultural land uses and corn land use in particular are associated with high rates of fertilizer and manure application (Powers 2007). To test this explanation, we formulated N models without a watershed land-use term and observed that model variance was transferred from watershed land use to the nutrient input terms total N input and P fertilizer (Appendix S1: Fig. S4). While the positive coefficient on total N input has a straightforward interpretation, the negative coefficient on P fertilizer is unclear. Rather than evidence of a true inverse relationship between P fertilizer and N (or evidence for stoichiometric interaction sensu Paerl et al. 2016), we interpret the negative coefficient on P fertilizer as evidence of either model misspecification (i.e., model fit was poor compared to the model with land use because N was very sensitive to land use)

or as evidence of multicollinearity among nutrient input variables (Appendix S1: Fig. S5). Thus, we think that it is likely that the removal of one of the key drivers of N (being land use) caused model variance to be transferred to nutrient input predictors generally such that the specific highlighting of P fertilizer is a result of noise rather than a true relationship.

Nutrient transport

An important category of predictors in our models was nutrient transport. For example, we found that baseflow was a significant predictor in all N but especially all P models. This is consistent with prior research at macroscales showing the sensitivity of lake nutrients to this metric (Collins et al. 2017). In contrast to baseflow, we found that watershed soil clay content was a significant predictor in all N models but not in any P models. Furthermore, we found that the coefficient on soil clay content was negative, which was contrary to our expectation, and prior research. It seems to suggest a negative correlation between clay content and N. However, upon closer inspection, we did not find evidence for such a relationship. Instead, we found evidence for a non-linear relationship, which may explain the negative coefficient on clay, whereby clay and TN were positively correlated over most of the range of watershed clay content but were negatively correlated in watersheds with very high soil clay content (>20%; Appendix S1: Fig. S7). This non-linear relationship may be an artifact of the specific non-random sampling of our lakes whereby the lakes with extremely high soil clay content watersheds happen to have extremely long water residence times leading to extensive removal of N loads due to denitrification (Groffman et al. 2009).

Overall, granular measures of agriculture were significant in both N and P models. However, the contribution of such measures relative to other non-agricultural predictors was greater for N models (Figs. 2, 3). One reason why granular measures of agricultural activity had a greater effect on N models may be that variation in N is less effectively captured solely by lake and watershed characteristics owing in part to the more complex nature of transformations in the nitrogen cycle. This finding is consistent with that of Collins et al. (2017) and Wagner and Schliep (2018) who found that lake depth coefficients were of a much higher magnitude for P relative to N. This is expected since depth strongly controls internal P loading (i.e., recycling), which is a dominant control on lake phosphorus dynamics (Søndergaard et al. 2013).

Regional variation in agriculture–nutrient relationships

The macroscale nature of our study motivated our second research question examining how relationships between agricultural activities and lake nutrients vary regionally. This is because recent research has shown that analyzing macroscale lake datasets without considering the possibility of regionally varying relationships runs the risk of drawing imprecise or incorrect conclusions because it can lump together lakes with fundamentally different responses to a given predictor variable (Qian et al. 2019). Additionally, we looked at this question because prior studies have shown regional variation in the relationship of lake nutrient concentrations to aggregate measures of agriculture (Wagner and Schliep 2018).

In our study, we found mixed evidence for regional variation in relationships with watershed land use, depending on the lake nutrient response variable. For N, we found evidence for regional variation whereby lakes in two of the 37 regions were more sensitive to changes in agricultural land use relative to other regions. The reasons for this elevated sensitivity are unclear, but one possible reason may be that watersheds in these more sensitive regions had higher median soil clay content than the median soil clay content of watersheds in less sensitive regions (Fig. 6). Higher soil clay content in particular may ultimately control the nitrogen content of field runoff because it is associated with more direct (i.e., tile) drainage. For example, maps produced by Capel et al. (2018*b*) suggest that our more sensitive regions correspond roughly with areas where field exports of nutrients are likely to bypass trapping by riparian buffers. As evidence of this association, data from Nakagaki and Wieczorek (2016) indicate that watersheds in these two sensitive regions had a unique combination of high soil clay content and extensive tile drainage (Appendix S1: Fig. S6).

For P, we found no evidence for regional variation in its relationship with watershed land use. This finding, that watershed land use can be modeled as a global (fixed) effect, is consistent with that of Taranu and Gregory-Eaves (2008), who found no statistically significant differences in region-specific relationships between lake P and agricultural land use. However, it is inconsistent with that of Wagner et al. (2011), who found regionally variable relationships between lake P and agricultural land use using a multilevel modeling framework. One reason that both our analysis and the Taranu and Gregory-Eaves (2008) study did not observe regional variation in the watershed land use vs. P relationship may be that P is so strongly controlled by lake depth that there is little additional explanatory power offered by including a watershed land use term. In addition, if lake P is controlled primarily by lake depth, which we can assume does not change with time, then our results may explain the finding of Oliver et al. (2017) that lake P trends are spatially consistent whereas lake N trends have distinct regional variability.

Management implications

Knowledge of differences in the drivers of lake N and P can support the design of effective and efficient policy approaches to maintain or improve water quality. For instance, our finding of regional variation in the relationship between lake TN concentrations and watershed land use in agriculture suggests spatial targeting of best

management practices (BMPs) to specific regions known to be highly sensitive (Holmes et al. 2016). In addition, our finding of strong relationships between lake TP concentrations and lake characteristic predictors contrasts with the strong relationships we observed between watershed land use and lake TN. Given that watershed land use, rather than lake characteristics, is a more feasible management target, our results suggest that the cost-effectiveness of BMPs could differ depending on whether the goal is to protect against excess N, P, or both (Paerl et al. 2016). For P, our analysis suggests that nutrient control policies are likely to be especially effective in shallow lakes and lakes with low baseflow (i.e., those with flashier hydrology). Conversely, phosphorus control in deeper lakes and reservoirs with long residence times will likely require recovery efforts in addition to prevention efforts due to the long time scales of stored (i.e., legacy) P (Powers et al. 2015). In contrast to P, our results show that lake TN concentrations are more sensitive to watershed land use. This suggests that policies to enhance the use of BMPs to reduce N inputs to lakes are likely to require a greater degree of stakeholder involvement, possibly through consideration of tradeoffs between land retirement and working lands programs (NRC 2010, Capel et al. 2018*b*).

Future research priorities

Due to a lack of temporally resolved data, our study focused on spatial patterns in sensitivity of lake TN and TP concentrations to measures of agricultural activity and did not examine the possibility that such relationships could be temporally variable. A consequence of this was that we assumed that relationships between lake N and P relative to agricultural drivers did not change over our data collection window (2000–2010). However, there are several instances where time may be important, and these would likely be fruitful areas for future research. For example, Lark et al. (2015) showed marked conversion of conservation reserve program (CRP) lands to cropland throughout the footprint of our study from 2008 to 2012. Such changes in land use could make it more difficult to quantify lake sensitivity to agriculture if relationships vary through time especially if relationships are subject to threshold effects (Renwick et al. 2008). A more subtle illustration of when time may be important is when field-scale nutrient export is highly dependent on episodic hydrology. For example, a number of previous studies have shown that field-scale nutrient export of N is greatest when a series of dry years is followed by a wet spring (Motew et al. 2017, Strickling and Obenour 2018). It might make sense then to organize modeling around whether lake watersheds are generally subject to slow flow, fast flow, or drain flow (Capel et al. 2018*b*) nutrient transport rather than solely taking a spatial regionalization approach (i.e., using HUCs). Barriers to more detailed temporal approaches include greater demands of spatiotemporally resolved data products. Overall, our results point to hydrology predictors like baseflow as an instance where we only have spatially coarse information and development of more granular estimates of watershed hydrology, possibly using the output of hydrology models, would likely improve future research efforts.

Conclusion

We show that granular measures of agricultural activity are related to both lake N and P and that these relationships are regionally variable for lake N. Taken together, our results suggest that lake TP concentrations are more strongly driven by lake characteristics; whereas, lake TN concentrations are more strongly driven by watershed land use. A consequence of our finding is that lake TP concentrations are largely predictable from lake-specific measures such as near-stream land use, lake depth, and transport metrics like baseflow; whereas, accurate predictions of lake N likely requires not only lake-specific information (including granular measures of agriculture) but also consideration of regional context due to complex regional variation of soil characteristics. Such differences in lake nutrient model sensitivity to measures of agricultural activity may affect the outcome of policies to enhance water quality depending on whether they focus on lake N or P.

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Supporting Information

Additional supporting information may be found online at: http://onlinelibrary.wiley.com/doi/10.1002/eap.2187/full

Data Availability

Data and code are available on Zenodo: https://doi.org/10.5281/zenodo.3754916