Received: 21 March 2017 | Accepted: 31 May 2017

DOI: 10.1111/gcb.13810

PRIMARY RESEARCH ARTICLE

WILEY Global Change Biology

Unexpected stasis in a changing world: Lake nutrient and chlorophyll trends since 1990

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Funding information

National Science Foundation, Grant/Award Number: 1065786, 1065818, 1401954; University of Wisconsin-Madison

Abstract

The United States (U.S.) has faced major environmental changes in recent decades, including agricultural intensification and urban expansion, as well as changes in atmospheric deposition and climate—all of which may influence eutrophication of freshwaters. However, it is unclear whether or how water quality in lakes across diverse ecological settings has responded to environmental change. We quantified water quality trends in 2913 lakes using nutrient and chlorophyll (Chl) observations from the Lake Multi-Scaled Geospatial and Temporal Database of the Northeast U.S. (LAGOS-NE), a collection of preexisting lake data mostly from state agencies. LAGOS-NE was used to quantify whether lake water quality has changed from 1990 to 2013, and whether lake-specific or regional geophysical factors were related to the observed changes. We modeled change through time using hierarchical linear models for total nitrogen (TN), total phosphorus (TP), stoichiometry (TN:TP), and Chl. Both the slopes (percent change per year) and intercepts (value in 1990) were allowed to vary by lake and region. Across all lakes, TN declined at a rate of 1.1% year^{-1}, while TP, TN:TP, and Chl did not change. A minority (7%–16%) of individual lakes had changing nutrients, stoichiometry, or Chl. Of those lakes that changed, we found differences in the geospatial variables that were most related to the observed change in the response variables. For example, TN and TN:TP trends were related to region-level drivers associated with atmospheric deposition of N; TP trends were related to both lake and region-level drivers associated with climate and land use; and Chl trends were found in regions with high air temperature at the beginning of the study period. We conclude that despite large environmental change and management efforts over recent decades, water quality of lakes in the Midwest and Northeast U.S. has not overwhelmingly degraded or improved.

KEYWORDS

eutrophication, hierarchical linear models, lakes, multiscaled drivers, nutrients, random forest, stoichiometry, water quality

1 | INTRODUCTION

Despite continuing efforts to reduce surface water nutrient inputs, environmental changes that influence, and most likely exacerbate, lake eutrophication are occurring simultaneously across multiple spatial scales. At the watershed scale, nutrient delivery to surface waters may be enhanced by ongoing land use changes that include urban expansion (Alig, Kline, & Lichtenstein, 2004), agricultural intensification (Lin, 2015; Matson, Parton, Power, & Swift, 1997; Rudel et al., 2009), and grassland conversion to biofuel crops (Wright & Wimberly, 2013). At broad scales, climate change is warming lakes (O'Reilly et al., 2015), and the increasing frequency of extreme precipitation events in many regions is likely transporting more nutrients to surface waters (Allan & Soden, 2008; Daloğlu, Cho, & Scavia, 2012). Though atmospheric nitrate deposition has declined in the United States, ammonia deposition is increasing, particularly in the agricultural Midwest (Du, de Vries, Galloway, Hu, & Fang, 2014). These environmental changes are not evenly distributed in time or space, but all are expected to exacerbate eutrophication conditions in surface waters.

Attempts to reduce nonpoint pollution to surface waters include both local agricultural management strategies and broad-scale policy changes, and there is limited understanding if these efforts translate to changes in water quality across regional to continental extents. Local agricultural management strategies are typically implemented at the scale of individual properties or watersheds (Shortle, Ribaudo, Horan, & Blandford, 2012; Wardropper, Chang, & Rissman, 2015), and case studies of these conservation strategies (e.g., no-till, riparian buffer establishment) have shown reduced nutrient loading to freshwaters (Her, Chaubey, Frankenberger, & Smith, 2016; Lowrance & Sheridan, 2005). Best management practices (BMPs) are highly variable in effectiveness, and there is evidence that these local conservation efforts do not improve water quality at broader spatial extents (Sharpley, Kleinman, Jordan, Bergström, & Allen, 2009; Tomer & Locke, 2011). In contrast to these local-scale management actions that are typically implemented in piecemeal fashion, broad-scale policies have the potential to influence water quality in a larger number of systems. For example, amendments to the Clean Air Act in 1990 to curb acid rain have reduced atmospheric nitrogen (N) deposition in the Northeast U.S. (Lehmann, Bowersox, & Larson, 2005), where modest reductions in surface water nitrate have been documented (Driscoll, Driscoll, Roy, & Mitchell, 2003). Given the substantial costs of efforts to manage water quality, e.g., the U.S. Department of Agriculture (USDA) spends $3.5 billion annually to incentivize agricultural conservation (Tomer & Locke, 2011), it is imperative to understand broad-scale changes in water quality and how they relate to management actions at different spatial scales.

How nutrient processing and retention within an individual lake are affected by these multiscaled mitigation efforts and ongoing environmental threats is a function of its specific morphology and hydrology (Edmondson, 1961; Vollenweider, 1975). To add to this complexity, N and phosphorus (P) have distinct biogeochemical cycles that may result in divergent responses to management actions (Gerson, Driscoll, & Roy, 2016; Stow, Cha, Johnson, Confesor, & Richards, 2015). Lake productivity can be N and/or P limited, which can alter the lake-specific response to changing nutrients (Elser et al., 2007). Further, in addition to absolute concentrations, relative concentrations (i.e., N:P ratios) may influence productivity or likelihood of harmful cyanobacterial blooms (Paerl et al., 2016). Lake and nutrient-specific processes that interact with environmental change further complicate our ability to quantify long-term trends in water quality.

Consistent with the expectation of complex responses to environmental change, several recent large-scale studies demonstrate the occurrence of contrasting water quality trends within and across regions and water quality parameters. For example, both increasing and decreasing water clarity has been documented within regions of the Midwest and Northeast U.S., but the majority of lakes exhibit no change (Canfield et al., 2016; Lottig et al., 2014; Olmanson, Bauer, & Brezonik, 2008; Peckham & Lillesand, 2006; Rose, Greb, Diebel, & Turner, 2017). Similarly, N concentrations among lakes in acid sensitive regions of Europe and North America have alternatively increased, decreased, or not significantly changed over the past three decades in response to reductions in N deposition (Garmo et al., 2014) and at the same time N has increased significantly in some of the world's largest lakes due to management efforts focused solely on P reduction (Finlay, Small, & Sterner, 2013). Conversely, P may accumulate faster than N in human-dominated lakes (Yan et al., 2016), and a recent nationwide survey of streams and lakes in the United States suggested that between 2007 and 2012, P increased while N did not change (Stoddard et al., 2016), though the mechanism driving this shift is not clear. Many of these multilake studies have limited temporal (e.g., 2007–2012 in Stoddard et al., 2016), spatial (e.g., state-specific trends in Olmanson et al., 2008), or system type (e.g., large lakes in Finlay et al., 2013) coverage, highlighting the need to assess change across the diversity of landscapes and lakes that match the scale of emerging environmental challenges.

We overcame many of the above data limitations through the use of the spatially and temporally extensive database for thousands of lakes in 17 Midwest and Northeast U.S. states, known as the Lake Multi-Scaled Geospatial and Temporal Database of the Northeast U.S. (LAGOS-NE). We evaluated changes in total nitrogen (TN), total phosphorus (TP), stoichiometry (N:P), and chlorophyll (Chl) over a 24-year period for 2913 lakes. We ask: (i) Have lake nutrient concentrations, stoichiometry, and Chl changed since 1990? (ii) What lake-specific and regional factors are related to water quality trends? (iii) Are Chl trends related to changes in N, P, or N:P?

To guide our analysis and interpretation, we generated a set of predictions about the spatial scale and direction of change in water quality parameters. The presence of ongoing environmental stressors and limited success of nonpoint management to date lead to the prediction of more increasing than decreasing trends in nutrient and chlorophyll concentrations. However, we also anticipated that water quality trends are not uniform in their direction or spatial scale of occurrence, reflective of differences in direction and scale of influence of drivers, interactions among these drivers, and the distinct biogeochemistry of N and P. For example, reductions in N deposition resulting from the Clean Air Act occur at broad spatial scales. We therefore expected declines in N for those regions where precipitation has been a major source of this nutrient to lakes, but not for regions with other sources of N to lakes (e.g., runoff in agricultural regions). Similarly, climate is changing at regional and subcontinental scales, so we predict that regions with increased precipitation and ample supplies of in situ nutrients (i.e., agricultural landscapes) will show regional-scale increases in lake nutrients. However, because management practices are variable and applied locally, and because P has low mobility relative to N, we expect high variability in P trends across all spatial scales. Finally, because both N and P can limit primary production in lakes, and because these two nutrients are often positively correlated (Downing & McCauley, 1992), we expect Chl trends to be positively correlated to nutrient trends.

2 | MATERIALS AND METHODS

All lake, landscape and climate data came from LAGOS-NE, a collection of lake ecosystems with supporting contextual information for a 17-state region of the United States including Minnesota, Wisconsin, Iowa, Missouri, Illinois, Indiana, Michigan, Ohio, Pennsylvania, New York, New Jersey, Connecticut, Massachusetts, Rhode Island, Vermont, New Hampshire, and Maine (Soranno et al., 2015). Nutrient, chlorophyll, and lake depth data came from LAGOS-NE_{LIMNO} (Version 1.054.1), a database that integrated field-based measurements of nutrients and physical properties from 54 government and university organizations on a subset of lakes across the study extent. Atmospheric deposition, climate, land use, and hydrologic data came from LAGOS-NE_{GEO} (Version 1.03). LAGOS-NE_{GEO} is a collection of spatially referenced measurements that provides contextual information for all lakes >4 ha in the study extent. Some lakes (<6% for each response) with nutrient or Chl data were <4 ha (Table 1) and were included in the trend analysis, but were not included in subsequent analyses that required contextual information. Because LAGOS-NE includes a census of all lakes >4 ha in the study extent (see additional file 9 in Soranno et al., 2015 for a description of lake inventory), we were able to assess how the ecological context of lakes with chemistry data (hereafter, "sample lakes") compared to the population of lakes in the region (hereafter, "census"). Additionally, because a major focus in creating LAGOS-NE was in compiling and integrating metadata for each dataset, we overcame a common problem that is found with simply downloading data from a government repository (e.g., the U.S. Environmental Protection Agency's STOrage and RETrieval Data Warehouse)—namely that as much as 50% of the data values can lack sufficient metadata to use the data effectively (Sprague, Oelsner, & Argue, 2017). A detailed description of how LAGOS-NE was built, including details on data sources and methods of metric derivation, can be found in Soranno et al. (2015).

2.1 | Nutrient data

We were interested in post-1990 water quality because improvements following the Clean Water Act were likely to have occurred prior to 1990, and any changes after 1990 are more likely to be a response to ongoing land use, climate, and atmospheric deposition changes. Long-term change in water quality was evaluated using TN, TP, and Chl concentrations. In instances where total Kjeldahl nitrogen (TKN) was reported, TN was calculated as the sum of TKN, nitrate, and nitrite (Smart, Reid, & Jones, 1981). Changes in lake stoichiometry (TN:TP) were also evaluated using concurrent measurements of TN and TP. All values were summer (June 15 through September 15) epilimnetic measurements. Annual summer average was used when more than one measurement was made per lake per year. Nutrient and Chl values are reported in micromoles and micrograms per liter, respectively, and were $\log_e$ transformed prior to analysis to accommodate the assumptions of normality and homoscedasticity of the linear model. For each response variable, we used the following criteria for a lake to be included in the trend analysis. Lakes were included if they had one or more observations in each period of 1990–2000 and 2001–2011. A small proportion of lakes had data through 2013; these data were included in the analysis, but were not used to determine if a lake was or was not included. Additionally, the two or more observations from each lake time series had to span a minimum of 5 years. That is, a lake with observations from 2000 to 2001 would not be included, whereas a lake with observations from 2000 to 2005 would be included.

2.2 | Lake context data

We evaluated potential trend drivers using contextual land use/land cover (LULC), climate, hydrology, deposition, and geomorphological data from LAGOS-NE_{GEO} (Table S1). Drivers were quantified at the lake and region levels. Lake-level drivers included LULC, topography,

TABLE 1 Characteristics of lakes used in the total nitrogen (TN), total phosphorus (TP), TN:TP, and chlorophyll (Chl) models

Summary	TN (μM/L)	TP (μM/L)	TN:TP (M)	Chl (μg/L)	Census (≥4 ha)
n lakes (*n* lakes ≥4 ha)	833 (788)	2,096 (2,037)	742 (701)	2,239 (2177)	51,107
n regions	50	58	44	62	66
Summer value	54 (20, 157)	0.5 (0.2, 2.3)	51 (25, 133)	6 (2, 46)	NA
Years/lake	5 (3, 15)	9 (3, 20)	5 (2, 16)	9 (3, 17)	NA
Lake area (ha)	44 (7, 546)	64 (10, 577)	39 (6, 469)	80 (11, 689)	10 (5, 75)
Max lake depth (m)	9 (4, 21)	10 (4, 22)	9 (4, 21)	10 (4, 24)	6 (3, 10)[a]
% Agriculture in watershed	48 (0, 81)	8 (0,72)	50 (1, 81)	16 (0, 75)	5 (0, 72)
% Urban in watershed	2 (0, 16)	1 (0, 10)	2 (0, 14)	1 (0, 18)	0 (0, 14)

Median values are reported, with corresponding 10th and 90th percentiles in parenthesis. When possible, summary statistics are provided for all lakes ≥4 ha in the study extent ("census"). Some lakes in the trend analysis were <4 ha, however, the random forest analysis was limited to lakes ≥4 ha.
[a]Census lake depth values based on predicted maximum depth (Oliver et al., 2016b).

and connectivity data derived at the watershed scale, as well as lake area and maximum depth. Region-level drivers included LULC, topography, connectivity, hydrology, climate, and atmospheric deposition data. The regional classification we used (4 digit hydrologic unit code or HUC 4, hereafter "region") came from the U.S. Geological Survey National Hydrography Dataset, which consists of nested river watersheds (Seaber, Kapinos, & Knapp, 1987) that effectively capture spatial structure in water quality data (Cheruvelil, Soranno, Bremigan, Wagner, & Martin, 2008). In our 17-state study extent, there are 65 HUC 4 regions with an average size of ~26,500 km^2. Where temporal driver data were available (atmospheric deposition and climate drivers), absolute values at the beginning (1990) and end (2010 for atmospheric deposition, 2011 for climate) of the time extent, as well as change through time, were included. Change through time was estimated using linear regression to assess monotonic changes in environmental drivers.

2.3 | Statistical analysis

We examined nutrient trends using hierarchical linear models (HLM; Gelman & Hill, 2007). We anticipated that local (e.g., lake depth) and regional (e.g., atmospheric deposition) drivers would create hierarchical structure in the data where observations within a lake would be more similar than observations across lakes, and lakes within regions would be more similar than lakes across regions. These two sources of variation (within and across lakes and regions) were accounted for in the HLMs by allowing the relationship between sample year and response (hereafter, "trend") to vary by lake and region (hereafter, lake-specific and region-specific trends or collectively "random effects"). Additionally, the model estimates a fixed effect that represents the average trend across all lakes in the analysis (hereafter, population-average trend). The mixed model approach uses partial pooling (Gelman & Hill, 2007), which is well-suited for the nutrient data that is not equally distributed across lakes and regions. For example, trend estimates for lakes or regions with low sample size or with a limited range of years sampled (and thus high uncertainty) will be shrunk toward the mean of trends in the region or across all lakes (e.g., population-average), respectively. Shrinkage toward the means also allows for analysis of the level 2 and level 3 trend estimates (e.g., number of lakes with significant trends) without correcting for multiple comparisons because HLMs already have less extreme (more conservative) estimates relative to traditional linear regression (Gelman, Hill, & Yajima, 2012).

The hierarchical nature of the data was formally assessed using unconditional 3-level models, where the first level, or observation level of the model is:

$$Y_{ijk} = \pi_{0jk} + e_{ijk} \tag{1}$$

where Y_{ijk} is the $\log_e$ transformed response in year i in lake j in region k, π_{0jk} is the mean response value of lake j in region k, and e_{ijk} is the residual error term, which was assumed to be normally distributed with a mean of 0 and variance σ^2. The second level, or lake level of the model is:

$$\pi_{0jk} = \beta_{00k} + u_{0jk} \tag{2}$$

where β_{00k} is the mean response in region k and u_{0jk} is the random lake effect, or the deviation of the lake mean from the region mean. We assumed the random lake effect was normally distributed with a mean of 0 and variance σ_π. The third level, or region level of the model is:

$$\beta_{00k} = \gamma_{000} + u_{00k} \tag{3}$$

where γ_{000} is the grand mean of the response and u_{00k} is the random region effect, or the deviation of the region mean from the grand mean. We assumed the random region effect was normally distributed with a mean of 0 and variance σ_β. We calculated the intraclass correlation coefficient (ICC) to estimate the proportion of the total variation resolved at each level of the model (Raudenbush & Bryk, 2002).

To address the hierarchical nature of the dataset when assessing change through time, Equations (1)–(3) were expanded to include a random time (random slope) effect,

$$Y_{ijk} = \beta_{0jk} + \beta_{1jk}T_{ijk} + e_{ijk}, \text{ with } e_{ijk} \sim N(0, \sigma^2) \tag{4}$$

where β_{0jk} is the response value in 1990 for lake j in region k (i.e., random intercept), T_{ijk} is the predictor year since 1990, and β_{1jk} is effect of the time for lake j in region k (i.e., random slopes). The second level of the model then becomes

$$\begin{aligned} \beta_{0jk} &= \beta_{00k} + u_{0jk}, \text{ with } u_{0jk} \sim N(0, \sigma^2_{0jk}) \\ \beta_{1jk} &= \beta_{10k} + u_{1jk}, \text{ with } u_{1jk} \sim N(0, \sigma^2_{1jk}) \end{aligned} \tag{5}$$

where β_{00k} and β_{10k} are the mean intercepts and slopes in region k, respectively, and u_{0jk} and u_{1jk} is the deviation of the intercepts and slopes of lake j from the mean intercepts and slopes in region k, respectively. The third level of the model is

$$\begin{aligned} \beta_{00k} &= \beta_{000} + u_{00k}, \text{ with } u_{00k} \sim N(0, \sigma^2_{00k}) \\ \beta_{10k} &= \beta_{100} + u_{10k}, \text{ with } u_{10k} \sim N(0, \sigma^2_{10k}) \end{aligned} \tag{6}$$

where β_{000} and β_{100} are the population-average (i.e., fixed) intercepts and slopes, respectively, and u_{00k} and u_{00k} are the region k deviations of the intercepts and slopes from the population-average means, respectively. Because the response variable was $\log_e$ transformed, the slopes were interpreted as percent change in the response variable per year. All statistical analysis were performed in R (R Core Team, 2015; see Appendices S1 and S2), and the linear mixed models were fitted using the *lmer* function in the package *lme4* (Bates, Maechler, Bolker, & Walker, 2015). We estimated means and confidence intervals for the fixed effects (population-average slopes and intercepts) and all random effects (lake and region-specific slopes and intercepts) with 1000 simulations using the *FEsim* and *REsim* functions in the *merTools* package (Knowles & Frederick, 2016).

To assess what types of lakes improved or degraded in water quality and to infer the drivers of change, we first categorized lakes as increasing, decreasing or not changing for each response based on whether the associated 90% confidence interval of the lake-specific trend overlapped with zero. We then used random forest (Breiman, 2001) analyses to predict the trend classification using lake and region-level predictors. Random forest is a regression tree analysis that creates a "forest" out of multiple "trees". For each tree in the forest, two-thirds of the data are used to create a tree, where a subset of the predictor variables is randomly permutated. The holdout third of the data ("out of bag") is used to test the performance of that tree. For each predictor variable, the difference in performance between trees with and without randomly permutated observations is used to determine the importance of the variable in predicting the response ("variable importance"). The overall performance of the forest is calculated using the out-of-bag classification error across all trees. Because the number of lakes was not balanced across the three response categories (increasing, decreasing, or no change), the sample size drawn for each response category was set to the minimum number of lakes in any category.

To assess how well lake-level vs. region-level drivers explained the variability in long-term change across lakes, we created three random forest models for each response using (i) lake-level predictors, (ii) region-level predictors and (iii) all predictors, and compared the out-of-bag (OOB) classification error rate. To interpret how individual drivers were related to long-term change, the "all predictors" models were pared down using a variable selection technique in the *VSURF* package (Genuer, Poggi, & Tuleau-Malot, 2016), where variables were removed through the "prediction" step. The reduced set of variables was then used in a final random forest model to evaluate top predictors according to mean decrease in accuracy. All random forest models were created using the *randomForest* package (Liaw & Wiener, 2002). Code used to generate all analyses and figures is included in the supplement (Appendices S1–S3), which sources the published nutrient and geophysical data used in this study (Oliver et al., 2016a). The code used for data processing, as well as the latest versions of the code included in the supplement, can be accessed on Github (https://github.com/limnoliver/CSI-Nutrient-Time-Series).

3 | RESULTS

The lakes included in one or more of the trend analyses (n = 2,913) represented 6% of the census lakes >4 ha in our study extent. The Chl and TP analyses had the most abundant data in terms of the number of lakes, number of observations per lake, and spatial coverage (Table 1). The lakes in our analyses were larger, deeper and had more human-impacted watersheds compared to the census lakes (Table 1, Fig. S1).

A large proportion of the variance in the observed nutrient and Chl values could be accounted for by clustering observations by lake and region. In other words, observations from the same lake or region were correlated. The percent of the total variance in the response that occurred at the lake scale ranged between 37% for TN and 47% for Chl. Between 15% (TN:TP) and 50% (TP) of variability in the response occurred at the region scale (Table S2).

3.1 | Change from 1990 to 2013

TN was the only response with a population-average slope (a trend across all lakes) in which the confidence interval did not include zero. Across all lakes, TN declined at a rate of 1.1% year^{-1} from 1990 to 2011 (Table 2). At the individual lake scale, 7%–16% of lakes were changing in any one of the responses, and the direction and magnitude of change varied across responses (Table 2; Figure 1). For example, 108 of 833 lakes in the TN analysis had long-term discernible trends, 94 of which were decreasing. TP change in individual lakes was more balanced, with 7% and 9% of lakes in the analysis increasing and decreasing, respectively. Only 8% of lakes had changing TN:TP. The lack of TN:TP change was also reflected in the relationship between TN and TP change for those lakes that were included in both nutrient analyses (Figure 2). Lake-specific TN and TP change was positively correlated, with only 14 of 757 lakes with TN and TP significantly changing in opposite directions. Twice as many lakes were increasing (10%) than decreasing (5%) in Chl.

TABLE 2 Estimated parameters from the 3-level mixed models, where concentration in 1990 (intercepts) and percent change per year (slopes) were allowed to vary by lake and region

Parameter	Description	TN	TP	TN:TP	Chl
Population-average	Intercept	4.2 (4.0–4.3)	−0.2 (−0.4 to 0.0)	4.0 (3.9–4.1)	2.0 (1.8–2.2)
	Time	−1.1 (−1.5 to −0.7)	−0.2 (−0.5 to 0.1)	−0.2 (−0.6 to 0.1)	0.3 (−0.2 to 0.8)
Lake	Intercept variance	0.27	0.42	0.22	0.84
	Time variance	0.01	0.02	0.03	0.06
	% Of lake-specific slopes <0, >0	11, 2	9, 7	5, 2	5, 10
Region	Intercept variance	0.43	0.56	0.11	0.68
	Time variance	0.02	0.01	0.01	0.04
	% Of region-specific slopes <0, >0	34, 0	19, 12	11, 0	11, 18
	Residual Variance	0.11	0.12	0.20	0.28

Values in parenthesis are 90% confidence intervals estimated by 1,000 posterior simulations.

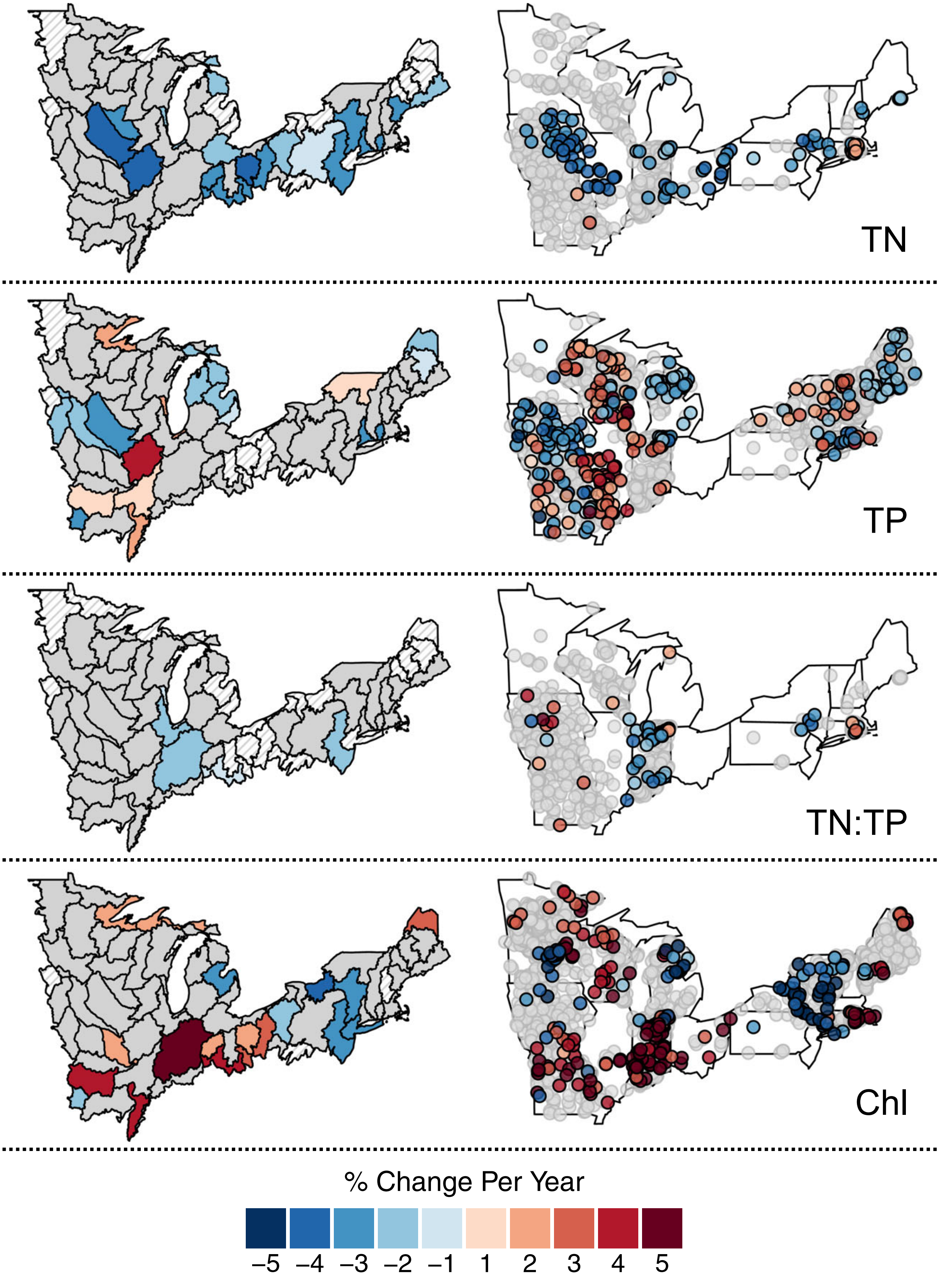

FIGURE 1 Region (left panel) and lake-specific (right panel) rates of change for total nitrogen (TN), total phosphorus (TP), TN:TP or Chl estimated by the mixed model. Rates of change are only shown for regions or lakes with trend estimates with 90% confidence intervals that did not overlap with zero. Gray regions or lakes are locations that did not have significant trends, and regions with no nutrient or chlorophyll data are white with gray hatching

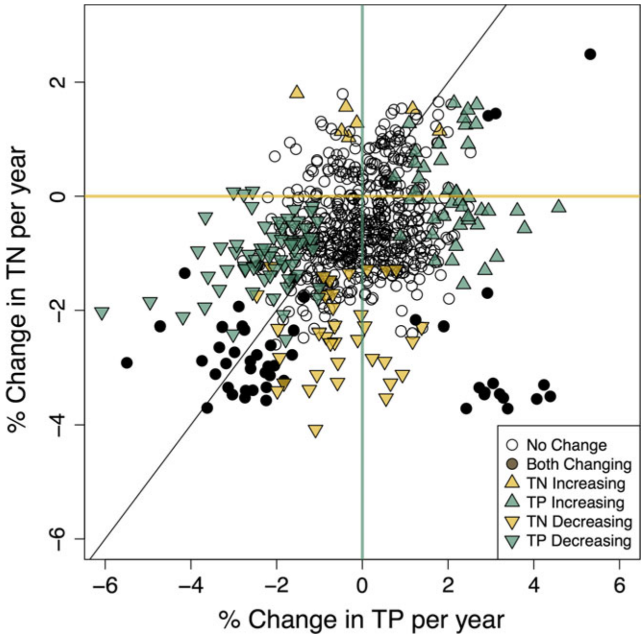

FIGURE 2 The relationship between estimated total nitrogen (TN) and total phosphorus (TP) trends for lakes with records of both nutrients (n = 757 lakes). The yellow horizontal line represents zero change in TN, the green vertical line represents zero change in TP, and the black line represents the 1:1 ratio of TN and TP change. Symbols are filled with color if the 90% confidence interval of the estimated rate of change from the mixed model was different from zero

Of the 2913 individual lakes that had observations of one or more of the response variables, 22% had significant trends in one or more responses. Of the 643 lakes that had observations of all four response variables, 51% had significant trends in one or more responses. The range in magnitude of change in individual lakes was similar for TN (−4.1% to 2.5% year^{-1}) and TN:TP (−3.8% to 4.0-% year^{-1}), and was greater for TP (−10.3% to 5.3% year^{-1}) and Chl (−8.7% to 12.9% year^{-1}).

Roughly 30% of regions were changing in TN, TP, or Chl, on average, while only 11% of regions had changing TN:TP (Table 2). For TN and TN:TP, the direction and geographic extent of change in regions matched that of lakes. A mid-latitude band from Iowa to Maine contained all regions that were changing for TN, all of which were declining (Figure 1). Regions with TP changes were less contiguous; regions in Iowa, Michigan, and Maine were mostly decreasing while regions with increasing TP were scattered between Missouri, Illinois, Minnesota, and New York. Many regions had lakes that were both increasing and decreasing in TP. There was a large band of regions with increasing Chl from Missouri to Ohio, while the regions with decreasing Chl were mostly limited to areas of Pennsylvania, New York, and Michigan.

3.2 | Drivers of change

In general, characteristics of the underlying data were not correlated with estimated rates of change in the lake (Fig. S2), with a few exceptions. Lakes with high TN (>140 μM) were almost exclusively not changing or decreasing in TN, and lakes with decreasing TN had more recent observations. TN:TP change was positively related to the mean TN:TP value. Generally, the estimated rate of change was more variable for lakes with fewer years of observation.

Chl trends were positively correlated to TN and TP trends (Figure 3). However, of the 661 lakes with TN, TP, and Chl records, Chl increased significantly in 133 lakes where there was no change in either TN or TP (Figure 3c). Both positive and negative trends in Chl were observed across the gradient in mean TN and TP (Fig. S3).

Region-level variables were better predictors of TN and Chl change than lake-level variables (Table 3). Regional predictors alone correctly classified TN change in 82% of lakes. In the TN:TP model, on the other hand, region-level predictors misclassified 71% of lakes. Lake-level predictors performed similarly across responses, with OOB error rates ranging from 32% for TP and 42% for TN. With all predictors, TN had the lowest OOB error rate (17%), while 49% of lakes were misclassified in the TN:TP model.

The variables most important in predicting each response largely reflected the performance of the lake vs. regional random forest models. Notably, region-level variables comprised all top four predictors of TN change, and most lakes that were declining in TN were in regions with high atmospheric N deposition in 1990 (Table 3; Figure 4a). TP and TN:TP, on the other hand, were best predicted by a combination of lake and region-level predictors, many of which were related to climate and N deposition changes, as well as agricultural land use (Table 3). The best predictor of TP change was change in precipitation over the study extent, where lakes with both positive and negative trends had less precipitation change compared to lakes that were not changing (Figure 4b). Regional temperature and base-flow index were the only predictors of Chl after variable selection (Table 3); lakes that were increasing in Chl were more likely to be in regions with high temperature in 1990 compared to lakes that were decreasing or not changing (Figure 4d).

4 | DISCUSSION

As expected, we found both increasing and decreasing nutrient and Chl trends in lakes in the Midwest and Northeast U.S., and there were differences in trends across our four measures of water quality. For example, TN has been declining on average since 1990, and negative TN trends were observed throughout the study extent. In contrast, both positive and negative TP and Chl trends were observed within and across regions. Though we could not connect specific mechanisms to water quality trends, these results suggest that N in lakes is responding similarly to controls that operate at broad spatial scales (i.e., atmospheric N deposition), and that local lake characteristics are not a primary control on TN. Alternatively, trends in TP and Chl were related to factors at multiple spatial scales. However, for a large majority of individual lakes (~78%) we did not observe a change in nutrients, stoichiometry or chlorophyll since 1990. We therefore conclude that despite the human-impacted and changing world in which these lakes are embedded, lake water quality, with respect to nutrient and Chl concentrations, has neither overwhelmingly degraded nor improved in recent decades.

The small proportion of lakes with increasing nutrients and/or Chl observed in this study, combined with the average decline in TN, may be interpreted optimistically to some. Mitigation efforts since 1990 could have reduced nutrient inputs to lakes; many regions in this study had declining atmospheric N deposition (data not shown; Lehmann et al., 2005), and from 1990 to 2006, the U.S. Environmental Protection Agency increased grants to states for nonpoint pollution management by 500% (Hardy & Koontz, 2008). Stable water quality over recent decades is supported by some broad-scale water clarity studies (e.g., Canfield et al., 2016; Lottig et al., 2014), and contrary to our expectations, nutrients were declining in some parts of the agricultural Midwest. Despite increased precipitation and temperature in the region that are expected to have negative impacts on water quality (Trolle, Hamilton, Pilditch, Duggan, & Jeppesen, 2011), nutrient control efforts may be "holding the line" (Moss et al., 2011).

On the other hand, twice as many lakes increased vs. decreased in Chl, which may be a more integrated signal of multiple stressors and worsening water quality. The low number of lakes with improved water quality, combined with evidence of continental increases in P in oligotrophic systems (Stoddard et al., 2016), and increases in sediment transport from agricultural watersheds with conservation programs (Heathcote, Filstrup, & Downing, 2013), suggests that the billions of dollars spent on management has not decreased nutrient concentrations in most lakes.

4.1 | Challenges in detecting change

We cannot completely rule out the possibility that a larger proportion of lakes are changing in N, P, and Chl, but were not detected in this study for several reasons. First, we may not have been able to detect trends in the lakes for which we have limited data. Water quality parameters are highly variable at the seasonal and annual scale due to a complex suite of physical, chemical, and biological processes that control lake nutrients, which could mask long-term trends (Reckhow & Stow, 1990). In fact, a time series analysis in reservoirs estimated that 13, 17, and >20 years of data for TN, TP, and Chl, respectively, would be required to detect a doubling of nutrient concentrations in 20 years (equivalent to 5% year^{-1}; Knowlton & Jones, 2006). Even in the subset of lakes that met those criteria in our study (16% of TN lakes, 21% of TP lakes, and 5% of Chl lakes), only 11%–17% of lakes were changing. Additionally, our mixed model approach weights individual lake trend estimates toward the estimates from those lakes and regions with more information, which should improve our ability to detect change in lakes with less information. We used average summer concentrations to

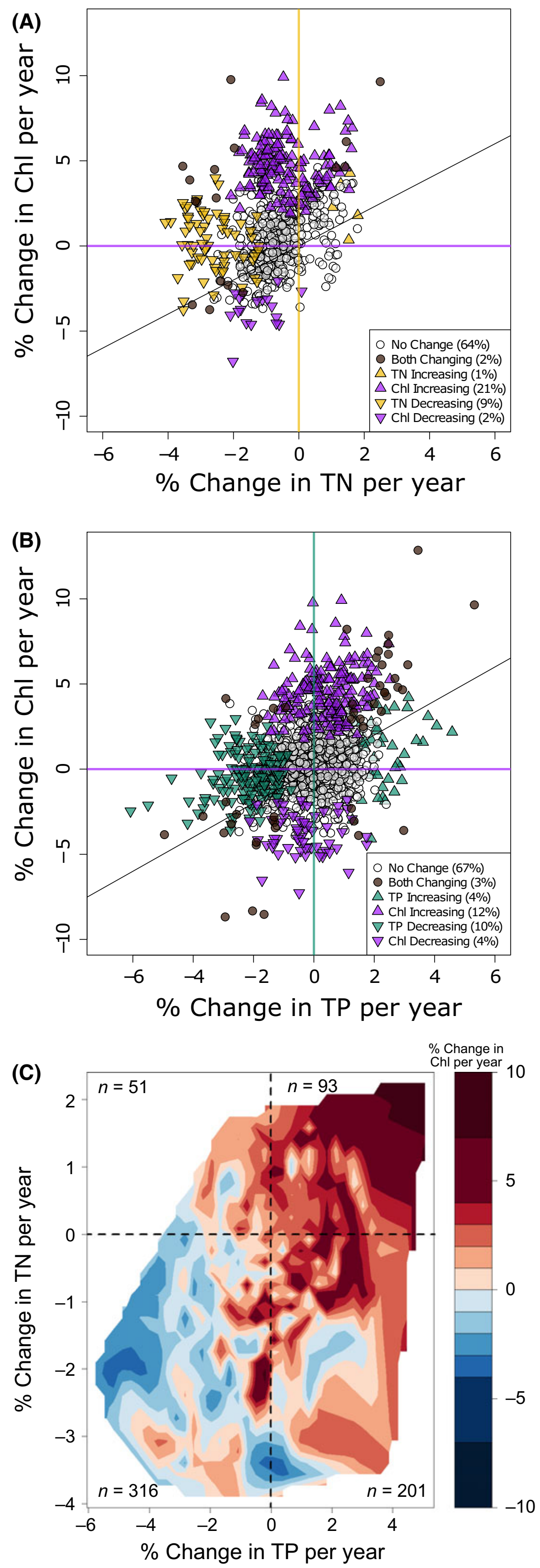

FIGURE 3 The relationship between lake-specific trends in Chl and nutrients for lakes with long-term records of both (a) Chl and total nitrogen (TN) (n = 730 lakes), (b) Chl and total phosphorus (TP) (middle; n = 1,435 lakes), and (c) Chl, TN and TP (bottom; n = 643 lakes). The vertical and horizontal lines in each panel represent zero change in the response variable on the x and y axis, respectively. The 45 degree line represents the 1:1 change ratio. In the contour plot (c), Chl change is represented by the color ramp. Numbers in the legend represent the proportion (a and b) or number (c) of lakes in each symbol category or quadrant

TABLE 3 The out-of-bag (OOB) classification error rate of random forest models using lake-level, region-level, or all predictors

Response variable	Lake predictors	Region predictors	All predictors	Top predictors
TN	42	18	17	Regional TN deposition 1990
				Regional % isolated lakes
				Regional runoff
				Regional avg. lake size
TP	32	43	34	Regional precipitation change
				WS % crops
				Regional baseflow
				Regional TN deposition 2010
				Regional precipitation 1990
TN:TP	41	71	49	Regional deposition change
				Maximum depth
				WS % pasture
				WS headwater stream density
Chl	36	29	28	Regional temperature 1990
				Regional baseflow

The error rate indicates the proportion of lakes the model could not correctly classify as increasing, decreasing, or not changing in the given response variable, and random classification would produce an error rate of 67%. The "all predictors" models column is the OOB error rate from the reduced model that underwent variable selection. Lake predictors included variables measured at the watershed (WS) scale, and region predictors included variables measured at the HUC 4 scale. The top five variables according to the mean decrease in accuracy are reported, unless fewer variables were left after variable selection. Each lake was classified as increasing, decreasing, or not changing based on the 90% confidence interval of the estimated change value from the mixed model.

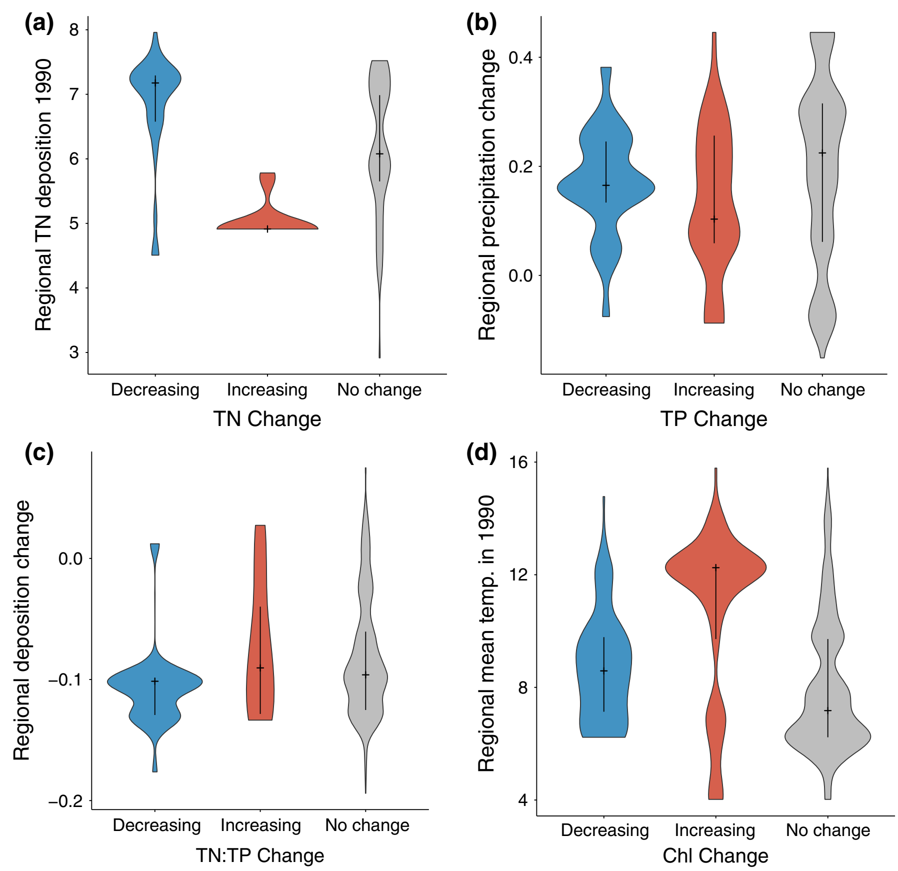

FIGURE 4 Violin plots showing the density distribution of the top predictor from the random forest models of (a) total nitrogen (TN), (b) total phosphorus (TP), (c) TN:TP and (d) chlorophyll (Chl) over the three responses (decreasing, increasing, no change). Lines within the violin plots represent the median and interquartile range. The categorical responses (increasing, decreasing, no change) were created by using the 90% confidence intervals of the estimates of change for each lake from the mixed model [Colour figure can be viewed at wileyonlinelibrary.com]

limit the effects of variability in lake stratification and environmental conditions, but in turn, may miss other important seasonal changes. Finally, we used linear models as a surrogate to capture net changes with time; however, more complex temporal patterns may exist and detecting them would require alternative analytical methods (Wagner, Irwin, Bence, & Hayes, 2013). The variability in water quality characteristics, using average summer concentrations, and linear methods may underestimate the number of lakes that are changing. However, the lack of change even for lakes with robust records, combined with the mixed model approach that uses partial pooling, supports the conclusion that most lakes have experienced minimal water quality change in recent decades.

There is a possibility that the lakes used in this analysis may not reflect long-term dynamics of nutrients across the entire population of lakes in our study extent. States often study lakes for specific reasons rather than conducting random sampling, and sample lakes are larger and have more human-modified watersheds relative to the proportion of lakes across the landscape (Wagner et al., 2008). We are confident that we captured the dynamics of urban and agricultural systems, as lakes in our study generally reflected the distribution and range of these land use types across the census lakes (Table 1, Fig. S1). Minimally disturbed and oligotrophic lakes may be increasing in P according to a recent assessment of nutrient trends from randomly chosen lakes across the United States, and atmospheric deposition was suggested as a potential cause of this change (Stoddard et al., 2016). Atmospheric deposition of N and P represents a larger fraction of total nutrient budgets in pristine watersheds, and so our analysis may miss important environmental changes that are not detectable in high-nutrient systems. Despite undersampling high forest cover systems (Fig. S1), our dataset contained 428 lakes with watersheds that met the land use portion of Stoddard et al.'s (2016) "minimally disturbed" definition (<5% agriculture, <1.5% urban, <2 km km^{-2} road density), and lake nutrient concentrations were not related to trends (Fig. S1). Our dataset is also biased by lake size where small lakes are underrepresented, though the sample lakes spanned the entire size gradient. Small lakes have different chemistry (Hanson, Carpenter, Cardille, Coe, & Winslow, 2007), physical processes (Read et al., 2012), and responses to climate change (Winslow, Read, Hansen, & Hanson, 2015) compared to large lakes, and we may not have captured long-term changes in these distinct and abundant systems.

4.2 | Drivers of change

Despite the lack of trends in a majority of lakes, for those 23% of lakes that are changing in nutrients, stoichiometry or Chl, changes can be large (from −10% to 13% year^{-1}). It is important to identify which lakes are susceptible to change, and what might be the cause of that change. Our random forest analysis attempted to identify the characteristics of the lakes that are changing, which may help infer which lake and context characteristics are associated with sites that are improving or degrading in water quality.

Two lines of evidence suggest that lakes in our study region are responding to atmospheric deposition changes that have occurred as a consequence of the Clean Air Act. Regions with negative lake TN trends also had high deposition in 1990 (Table 3, Figure 4a) and regions with high deposition in 1990 had the largest decreases in atmospheric deposition (data not shown). Additionally, lakes with negative TN:TP trends tended to be in regions with the largest deposition declines (Figure 4c). While it is not universal, the link between declines in N deposition and declines in surface water N concentrations has been made for lakes in the Adirondacks Mountains in New York since 1990 (Driscoll et al., 2003), and over the past decade in New England lakes (Strock, Nelson, Kahl, Saros, & McDowell, 2014). Notably, lakes with the largest declines in TN were those with observations that skewed toward the second half of our study (post 2000), consistent with the delayed surface water responses to reductions in N deposition reported by Strock et al. (2014).

Though atmospheric deposition was the top predictor of the random forest analysis, it seems that changes in atmospheric deposition cannot be the only driver of widespread TN declines in lakes. In some regions, surface water nitrate concentrations have not responded strongly to declines in deposition (Garmo et al., 2014; Skjelkvåle et al., 2005), and nitrate leaching from N-saturated watersheds can increase even under constant N deposition (Curtis, Evans, Helliwell, & Monteith, 2005). Calcium additions to artificially induce acid rain recovery converted an experimental watershed from an N sink to source, suggesting future ecosystem responses to declines in atmospheric deposition may include N increases in surface waters (Rosi-Marshall, Bernhardt, Buso, Driscoll, & Likens, 2016). Additionally, N declines were observed in agricultural regions with extremely high TN concentrations (e.g., Iowa), where positive ammonium deposition trends have offset negative nitrate deposition trends (Li et al., 2016; Stoddard et al., 2003), and N deposition likely comprises a small fraction of the total N budget for each lake. Results from the random forest analysis suggest that TN changes might also be affected by regional land use, hydrology and connectivity and warrant further study.

In contrast to TN, our results show that factors related to climate change and land use may be altering TP concentrations in the small percentage of lakes that displayed TP trends. Using static (e.g., land use) rather than more relevant temporally dynamic (e.g., land use practices) predictors, combined with the overall lack of predictive ability of the TP random forest models, makes it difficult to discern the drivers of TP trends in this region. There is evidence that increases in precipitation increase P loading to lakes (Lathrop, Carpenter, Stow, Soranno, & Panuska, 1998). But on average, lakes with positive TP trends in our study had lower precipitation changes than lakes that were decreasing or not changing in TP. Annual total precipitation was used in our study, which may mask stronger seasonal changes in precipitation that disproportionately affect P delivery to lakes, such as winter and spring precipitation (Tiessen et al., 2010). Additionally, P transport to some lakes is tightly linked to extreme precipitation events rather than annual precipitation (Carpenter, Booth, Kucharik, & Lathrop, 2015), which was not captured in our study. Likewise, observed increases in TP in lakes and streams in the United States between two time points could not be linked to precipitation differences between the two years (Stoddard et al., 2016).

Our study shows that across the Midwest and Northeast U.S., the drivers of long-term change are different for TN and TP, and that the drivers are occurring at different spatial scales. The differences in lake-specific vs. regional controls of TN and TP match our biogeochemical understanding of the two nutrients. Nitrogen is transported to lakes mostly in dissolved form and can be transported long distances in the atmosphere and groundwater. Alternatively, P readily sorbs to particles and is more related to local surface water transport. Phosphorus is stored in soil organic matter and sediment, and there is often a lag between P loading to a watershed and responses in surface waters, and trends in each lake may reflect the specific land use histories and management of individual watersheds (Powers et al. 2016), which is difficult to quantify at this spatial scale. Differences in the spatial patterns, magnitude, and direction of trends observed in this study may in part be a reflection of differing biogeochemical cycles of N and P, which in this case, has led to differing responses to environmental change.

4.3 | Ecological relevance of change: relationship between nutrient and Chl trends

Reducing algal production is often the lake management endpoint, and decreasing P and/or N can reduce primary production in surface waters (Conley et al., 2009; Paerl et al., 2016; Schindler, 2012). Though TN and TP trends were both positively correlated to Chl trends, the contour plot (Figure 3c) shows vertical bands, suggesting Chl responded primarily to changes in TP. The magnitude of change in nutrients and Chl can also be used to infer if trends are ecologically meaningful. For example, lakes in Iowa with declining TN (n = 36 of 96) had a median trend of 3.1% year^{-1} from data that spanned 19 years, with a median shift in TN from 193 to ~80 μM/L. Lakes with TP declines in Iowa (n = 45 of 97) had a median shift from 3.6 to 2.1 μM/L. According to trophic state classifications, these reductions are large enough to move lakes from eutrophic to mesotrophic system (Dodds, Jones, & Welch, 1998). The reductions in nutrients apparently did not promote a similar shift in algal biomass, where only eight of 96 lakes in Iowa had negative trends in Chl. This example of a lack of Chl response to nutrients, as well as results from the random forest analysis, suggests that other emerging environmental changes are influencing trophic state in lakes.

A positive relationship between temperature, algal growth, and harmful algal blooms is well documented (O'Neil, Davis, Burford, & Gobler, 2012), and lakes with increasing Chl were located in the warmest regions at the start of the study period (1990). Though these regions did not have the largest increases in temperature (data not shown), warmer temperatures can enhance the photosynthetic response to nutrient enrichment (Wyatt et al., 2015), and the exponential metabolic response to temperature can create differential responses to climate change across gradients in mean lake temperature (Kraemer et al., 2016). Chl trends may therefore be an integrative response to nutrient and climate changes, and according to Chl trends presented here, roughly 10% of lakes and 18% of regions across our study extent have degraded in water quality since 1990.

As low points in the landscape, lakes integrate environmental changes in their watersheds, and therefore act as sentinels of change. In the United States, 64% of lake acres are estimated to be impaired and cannot support the designated use, and states list ongoing human pressures in the form of atmospheric deposition and agricultural activities as top sources of impairment (U.S. EPA, 2009). Climate change is likely to exacerbate eutrophication of surface waters (Moss et al., 2011). Even when nutrient sources are partially or completely removed, recovery of lakes after nutrient reductions is highly variable and can take years to decades (McCrackin, Jones, Jones, & Moreno-Mateos, 2017), highlighting the importance of long-term efforts that monitor water quality. In the Midwest and Northeast United States, lakes are facing drivers acting to both improve and degrade water quality, and as such, have remained relatively unchanged in the last 20 years in regards to nutrients and chlorophyll. Our study highlights the potential for N, P, and Chl to have differing responses to broad-scale environmental change. Identifying directional, mechanistic responses of biogeochemical cycles to the various aspects of climate change is a priority for understanding how water quality will change in a warmer, more extreme world.

ACKNOWLEDGEMENTS

This project was possible through funds from the National Science Foundation (1065786, 1065818, 1401954) and the University of Wisconsin-Madison Dissertation Completion Fellowship. This manuscript is GLERL contribution number 1857. We thank the rest of the CSI Limnology team who built LAGOS-NE and provided valuable feedback on this manuscript. We also thank many data providers that contributed to LAGOS-NE. Any use of trade, firm, or product names is for descriptive purposes only and does not imply endorsement by the U.S. Government.

AUTHOR CONTRIBUTIONS

SKO, PAS, EHS, and SMC contributed to the ideas and conceptual framework of this manuscript. SKO and TW designed the statistical analyses, and SKO performed the statistical analyses. SKO created the figures and tables. SKO wrote the manuscript, while EHS, PAS, and SMC provided portions of the text. All authors contributed critical discussions, reviews, and revisions of the manuscript.

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SUPPORTING INFORMATION

Additional Supporting Information may be found online in the supporting information tab for this article.

How to cite this article: Oliver SK, Collins SM, Soranno PA, et al. Unexpected stasis in a changing world: Lake nutrient and chlorophyll trends since 1990. *Glob Change Biol*. 2017;23:5455–5467. https://doi.org/10.1111/gcb.13810