Research Communications

No evidence of widespread algal bloom intensification in hundreds of lakes

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Running heads:
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Trends in algal bloom intensification

Algal blooms, the rapid proliferation of algal biomass often to nuisance or harmful levels, diminish aquatic ecosystem services. Freshwater blooms can cause substantial economic damage by interrupting water supply, limiting recreation, and reducing property values. The interaction between eutrophication and climate change has been hypothesized to drive widespread intensification of blooms in inland waters, although there is little empirical evidence that this trend is pervasive. Here, we show that bloom intensification in inland waterbodies – defined as trends in chlorophyll-*a* of increasing bloom magnitude, severity, or duration – has not been widespread for hundreds of lakes in the US. Only 10.8% of the 323 waterbodies analyzed had significant bloom intensification. Conversely, 16.4% of the waterbodies had significant decreasing trends during the same period. While it is encouraging that bloom intensification is not currently widespread, continued efforts toward aquatic ecosystem protection and restoration are imperative for maintaining ecosystem services into the future.

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Severe algal blooms threaten ecosystem and human health, resulting in billions of dollars in economic loss (Dodds *et al*. 2009). Blooms not only diminish the recreational value of lakes and reservoirs (Angradi *et al*. 2018), some common blooming species also produce toxins that are harmful or deadly (Carmichael 2001). Understanding how blooms in inland waters are responding, both in their ubiquity and severity, to global-scale changes is therefore crucial for mitigating their economic and ecological harm.

Global-scale anthropogenic disturbance of the nitrogen (N) and phosphorus (P) cycles has resulted in widespread eutrophication of inland waters (Smith 2003). Climate change is also modifying the hydrologic cycle, potentially exacerbating the eutrophication of surface waters, and creating favorable conditions for cyanobacterial growth (Paerl and Paul 2012). Moreover, climate change is increasing inland water temperatures (O'Reilly *et al*. 2015), influencing thermal stratification (Kraemer *et al*. 2015), and lengthening the ice-free period in temperate and high latitude lakes (Hewitt *et al*. 2018), all of which can favor increased phytoplankton growth, depending on lake characteristics (Taranu *et al*. 2012; Richardson *et al*. 2018). Consequently, it has been hypothesized that the interaction of accelerated eutrophication and climate change has led to the widespread intensification (that is, increased magnitude and severity) of algal blooms in lakes and reservoirs (Elliott 2012; O'Neil *et al*. 2012; Chapra *et al*. 2017). However, some evidence conflicts with this hypothesis (Kraemer *et al*. 2017; Oliver *et al*. 2017; Ho *et al*. 2019).

Coincident with the climate-change intensification hypothesis is increased media attention (Lyytimaki 2012) and growing public awareness of algal blooms, creating the perception that blooms are broadly intensifying in inland waters. To test whether empirical evidence matches this perception, we analyzed time-series of chlorophyll-*a* – a proxy for algal biomass – in 323 lakes across 11 states in the US Northeast and Midwest. The lakes ranged in size from 1.3 ha to more than 100,000 ha, encompassed oligotrophic to hypereutrophic conditions, and varied in watershed land use. Specifically, we investigated changes in algal bloom *magnitude*, *severity*, and *duration* (Figure 1) over more than a decade in each lake. As these variables can change independently and have distinct effects on ecosystem services, we evaluated trends in all three metrics in order to fully investigate algal bloom intensification in lakes. In addition, given the hypothesized interaction of eutrophication and climate change, we evaluated if lake characteristics and climate trends correlated with bloom trends.

Methods

We defined three bloom metrics to evaluate trends in algal bloom intensification: *magnitude*, *severity*, and *duration*. Increasing bloom *magnitude*, defined as a positive trend in annual mean chlorophyll-*a* concentration, reflects an increasing likelihood that ecosystem services are diminished due to algal biomass accumulation. An increase in bloom *severity* (positive trend in the 95th percentile of chlorophyll-*a* concentrations) suggests an increased likelihood of severe consequences from the bloom event, such as fish kills or toxin exposure. Finally, an increase in the *duration* of a bloom event, or amount of time chlorophyll-*a* concentrations exceed a water quality impairment threshold each season, is a measure of the increasing period of potential economic loss each year due to the bloom. We used region-specific chlorophyll-*a* concentration thresholds to establish when lakes transition from low to marginal recreational value based on Angradi *et al*. (2018). Each of the three bloom metrics was used to determine the percentage of lakes experiencing changes in algal blooms over a decade or more.

Assessing trends in the bloom metrics requires long time-series of algal biomass with sufficiently frequent sampling. Using a rarefaction analysis of 31 lake-years of daily algal pigment data (WebFigure 1), we determined that sampling approximately once every 14 days was an adequate balance between capturing the dynamics of the bloom metrics during a season while allowing for a large number of lake time-series to be included in the analysis. Time-series of chlorophyll-*a* for this analysis were required to be 10 years or longer in order to identify long-term trends in the bloom metrics instead of shorter term, spurious trends.

In total, we analyzed chlorophyll-*a* time-series in 323 lakes located in the contiguous US (Soranno *et al*. 2015, 2017) for interannual trends in the bloom metrics. Time-series lengths ranged from 10 to 42 years, with a median length of 14 years. Trend analysis was performed by fitting a generalized least-squares linear regression of chlorophyll-*a* against time, with model error having a first-order autoregressive correlation structure to control for temporal autocorrelation. We also tested whether the interannual pattern of the bloom metrics in each lake were better characterized by a quadratic function; because none of the trends in any lake were better described by a quadratic function (difference in Akaike information criteria [ΔAIC] < 2; Burnham and Anderson 2002), linear trends were used for all further analyses. Finally, we evaluated whether time-series length affected the distribution of trend coefficients of the three bloom metrics by examining subgroups of the dataset based on bins of time-series length (see WebPanel 1 for further details). The fraction of lakes with a positive or negative trend in bloom indicators was similar regardless of time-series length except for the very few time-series that exceeded 30 years, which tended to have more negative trends (WebFigure 2). No relationship was detected between bloom trends and starting year of the time-series.

We tested how lake physical characteristics (eg surface area), biogeochemistry (eg N:P ratio), climate change (ie temperature and precipitation trends), and ecoregion correlate with trends in the three bloom metrics using linear mixed effects regression and information-theoretic model selection. Specifically, we fit sets of models where a bloom metric trend was the response variable and predictor variables included lake surface area, maximum depth, drainage ratio, time-averaged chlorophyll-*a*, time-averaged N:P ratio, temporal trends in total N, temporal trends in total P, temporal trends in the 95th percentile of daily precipitation, and temporal trends in mean daily maximum temperature as fixed main effects. The US Environmental Protection Agency Level-II ecoregion were a random effect on the intercept (the lakes were in three ecoregions: 5.3 – Atlantic highlands, 8.1 – mixed wood plains, and 8.4 – Ozark Appalachian forest). All two-way interactions with time-averaged chlorophyll-*a* were also considered. We fit all combinations of models and selected the model that best balanced explanatory power and parsimony using AIC corrected for small sample sizes (AICc), and used likelihood ratio tests to evaluate the importance of random effects of ecoregion on model intercepts. As many models had similar AICc values, we also considered the importance of each covariate, which was computed by summing the AICc weights for all models containing each covariate. Due to missing values for covariates, regression analyses were performed on a subset of 104 (magnitude and severity bloom metrics) and 82 (duration bloom metric) lakes.

Results

No evidence of widespread algal bloom intensification was detected in the hundreds of lakes included in our analysis. Of the 323 chlorophyll-*a* time-series evaluated, only 10.8% of lakes were experiencing algal bloom intensification during the period of observation based on significant ($P < 0.05$) positive trends in one or more of the bloom metrics (Figure 2). Nearly 1.5 times as many lakes exhibited declining trends in algal bloom metrics than had increasing trends.

A total of 16.4% of the lakes had significant negative trends (*P* < 0.05) in at least one bloom metric, with two-thirds of those lakes having significant trends in two or more metrics.

An increase in bloom magnitude (annual mean chlorophyll-*a*) was the most common positive trend among the bloom metrics for lakes, with 9.3% of lakes significantly increasing in intensity. Markedly fewer lakes had significant positive trends in bloom severity (5.0%) or bloom duration (3.7%), and both of these metrics had fewer positive trends overall, regardless of significance. Of the lakes with significant positive trends in one bloom metric, only half also had positive trends in other metrics. Consequently, considering multiple metrics further weakens the evidence for widespread bloom intensification in lakes. As for lakes with significant negative trends, approximately two-thirds (~66.0%) of the lakes had significant negative trends in more than one bloom metric. There were no instances in which a lake had a significant positive trend in one metric and a significant negative trend in another.

Time-averaged lake chlorophyll-*a* (ie mean chlorophyll-*a*), lake surface area, precipitation trends, and ecoregion were important predictors of trends in magnitude and severity of algal blooms (Figure 3). The top models for magnitude and severity bloom trends explained 23% and 18% of variance, respectively. Including random effects of ecoregion on model intercepts greatly improved model fits (likelihood ratio test; magnitude: *P* = 0.0004, severity: *P* = 0.0087). However, no combination of covariates explained an appreciable amount of variability in bloom duration trends, and therefore models for bloom duration were not considered further.

The trend coefficient for bloom magnitude and severity became increasingly negative with increasing mean chlorophyll-*a* (Figure 3, a and e), while the trend coefficients increased with lake surface area (Figure 3, b and f). These variables also had the highest variable importance in the models (WebFigure 3). In addition, the bloom magnitude trend coefficient became increasingly negative as precipitation intensified (Figure 3c). There was also a positive interaction between mean chlorophyll-*a* and precipitation intensification, such that lakes with high mean chlorophyll-*a* that were experiencing precipitation intensification had increasing trends in bloom magnitude, while lakes with high mean chlorophyll-*a* experiencing precipitation declines had stronger decreasing trends in bloom magnitude (Figure 3d). Finally, there was a significant effect of ecoregion on the intercept of all these relationships, indicating that the baseline value in trend coefficients differs significantly among the regions.

Discussion

Algal blooms are a global problem with severe consequences for aquatic ecosystem services. Currently, the overwhelming narrative is that algal blooms are growing worse around the globe; however, our analysis of over 300 lakes revealed that there has been limited algal bloom intensification in lakes and reservoirs in recent decades in midwestern and northeastern US lakes. Instead, we found that many more lakes were improving with regards to algal bloom occurrence. These results shed new light on the previously assumed "widespread" pattern of algal bloom intensification.

A substantially smaller percentage of lakes in our dataset experienced algal bloom intensification compared to a recent analysis of 71 globally distributed large (>100 km^2) lakes (Ho *et al*. 2019). In the Ho *et al*. (2019) analysis, 31% of the lakes significantly ($P < 0.1$) increased in peak summertime bloom intensity (defined as severity in the present study); this is nearly five times greater than the 6.5% of lakes in the present study that increased in severity at the same significance level. Although our results appear to be in stark contrast to those of the global large lake analysis, the larger lakes included in the present study were more likely to exhibit increases in bloom magnitude and severity. This aligns with the pattern that a higher proportion of large lakes (>100 km^2) had increasing trends in bloom severity (Ho *et al*. 2019). However, given the numerical dominance of small lakes globally (Verpoorter *et al*. 2014), our finding that smaller lakes are more likely to have a negative trend in both bloom magnitude and severity supports the conclusion that bloom intensification is not widespread.

Our results are also consistent with other studies of lakes in the US that found a similar lack of widespread increase in chlorophyll-*a* and nutrient concentrations (Oliver *et al*. 2017). Approximately 25% of our study lakes had total P concentrations within the range likely to yield large changes in cyanobacteria biomass in response to changing nutrient concentrations (20–100 μg L^{-1}; Carvalho *et al*. 2013). However, there were not substantial trends in total P concentrations for lakes in the present analysis, likely contributing to the lack of widespread intensification of algal blooms observed in our study.

In addition to the few lakes that significantly increased in the bloom metrics, we discovered that even more lakes had significantly decreased. The 16.4% of lakes for which there was a significant negative trend in one or more bloom metrics was double the proportion of large lakes, globally (Ho *et al*. 2019). One possible reason for this disparity may be that our study lakes are all located in the US, where in 1972 the Clean Water Act was enacted to regulate surface water pollution, including eutrophication. We performed an ad hoc Internet search for newspaper articles and resource management reports to estimate a lower bound on the number of lakes with significant negative trends in the bloom metrics that were subject to active or recent restoration efforts. We found that at least 64.4% of the 53 lakes with significant negative trends in at least one bloom metric had undergone some degree of in-lake or watershed restoration, or that restoration activities were planned. Although other countries and governing bodies (eg the EU Water Framework Directive) have surface water regulations similar to the US Clean Water Act, some countries do not have regulations for surface waters or have only recently implemented national policies (Zhou *et al*. 2017). This disparity in regulations could contribute to the higher percentage of lakes experiencing recovery in our study compared to the global analysis of Ho *et al*. (2019). In addition, we found that lakes with a higher mean chlorophyll-*a* concentration tended to decline in both bloom magnitude and severity; this may be a result of eutrophic lakes being more likely to have undergone restoration or nutrient management to curb algal production due to their high nutrient concentrations.

Changes in climatic variables may also be driving algal bloom trends. The interaction of water temperature with trophic state has been important for explaining patterns of phytoplankton biomass in other regions (Rigosi *et al*. 2014; Kraemer *et al*. 2017). While we did not identify an effect of temperature on algal bloom intensification, the trend in 95th percentile of daily precipitation had a significant interactive effect with overall mean chlorophyll-*a* concentration, and therefore affected trends in algal bloom magnitude. For lakes where precipitation was not changing, there was a stronger decline in the trend in bloom magnitude for lakes with a higher mean chlorophyll-*a* concentration. However, lakes with a higher mean chlorophyll-*a* concentration that were also experiencing declining precipitation intensity had an even sharper decline in bloom magnitude, while those experiencing precipitation intensification had a marginally positive trend in magnitude. As such, it is possible that the effect of nutrient management efforts could be magnified for watersheds experiencing less intense precipitation, but could be overcome and potentially reversed in watersheds experiencing precipitation intensification.

The complex interaction of nutrient loading and the manifestation of climate change across scales makes it difficult to suggest a uniform management solution for controlling algal blooms (Richardson *et al*. 2018). What our analysis does reveal, however, is that bloom magnitude is susceptible to changes in extreme precipitation events, particularly in eutrophic lakes. The trends in extreme precipitation events may be modifying the quantity and timing of nutrients delivered to lakes (Carpenter *et al*. 2015), influencing the magnitude of blooms. Wind-induced mixing of the water column and flushing from storm events may also alter phytoplankton dynamics (Stockwell *et al*. 2020). To combat storm effects, management actions might focus on mitigating nutrient runoff and erosion in the watershed during large precipitation events and consider strategies that minimize storm-induced internal loading processes, such as sediment resuspension.

The anthropogenic acceleration of eutrophication in surface waters, including coastal areas, is a global phenomenon (Smith 2003). Although our analysis provides no evidence of widespread intensification of algal blooms in lakes in recent decades, drivers of global change will continue to influence the complex biological and environmental processes that affect algal blooms, and thereby the ecosystem services that the affected waterbodies provide. As such, it is necessary to continue efforts to reduce eutrophication, promote restoration, and adaptively manage and protect inland surface waters to prevent deterioration now and into the future.

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Data availability statement

The data products and analysis code are available on Zenodo at https://doi.org/10.5281/zenodo.5496240.

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Supporting Information

Additional, web-only material may be found in the online version of this article at

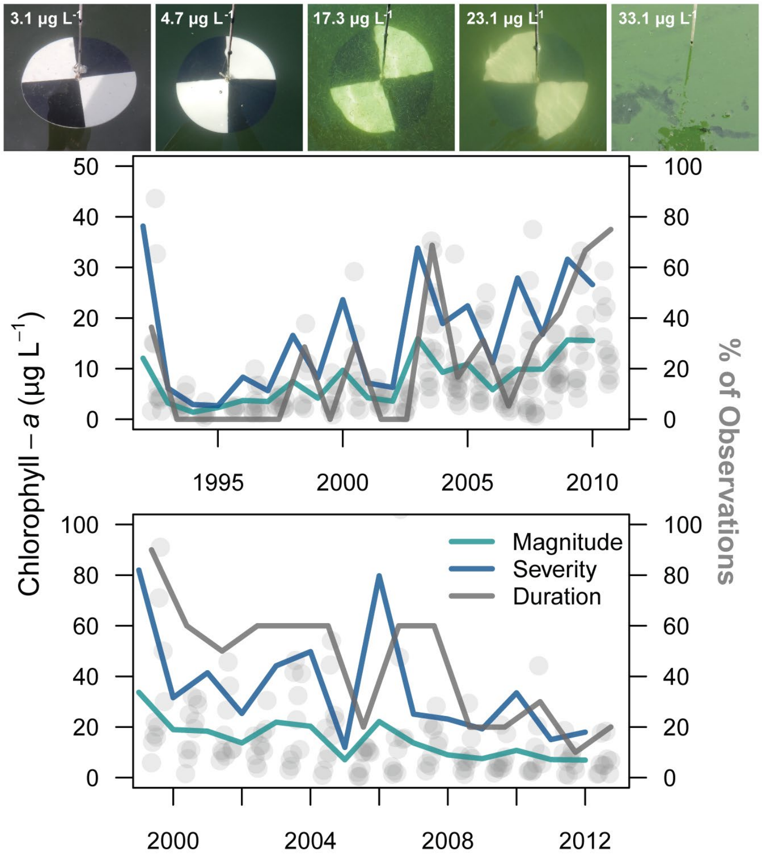
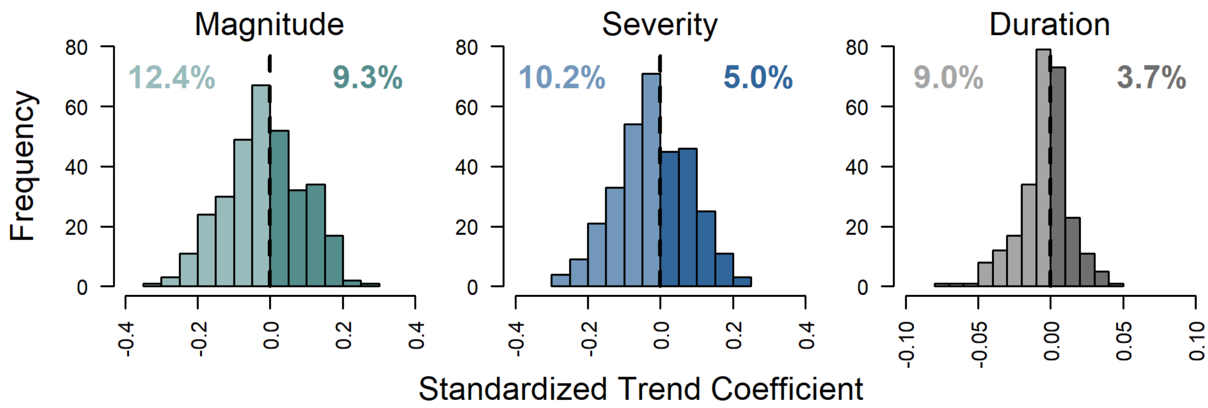


Figure 1. Time-series of chlorophyll-*a* concentrations (circles) and bloom metrics (lines) in two lakes that have (top panel) significantly increased in magnitude, severity, and duration and (bottom panel) significantly decreased in the three bloom metrics. The images at the top are of Secchi disks suspended at 0.2 m below the surface and the corresponding chlorophyll-*a* concentrations in the water column at that time. The images were taken from various lakes in Iowa from 2018 to 2020 and are meant to illustrate a gradient of chlorophyll-*a* concentrations within lakes typical of those included in our analysis.


Magnitude
Severity
Duration
Frequency
80
60
40
20
0
12.4%
9.3%
10.2%
5.0%
9.0%
3.7%
-0.4
-0.2
0.0
0.2
0.4
-0.10
-0.05
0.00
0.05
0.10
Standardized Trend Coefficient

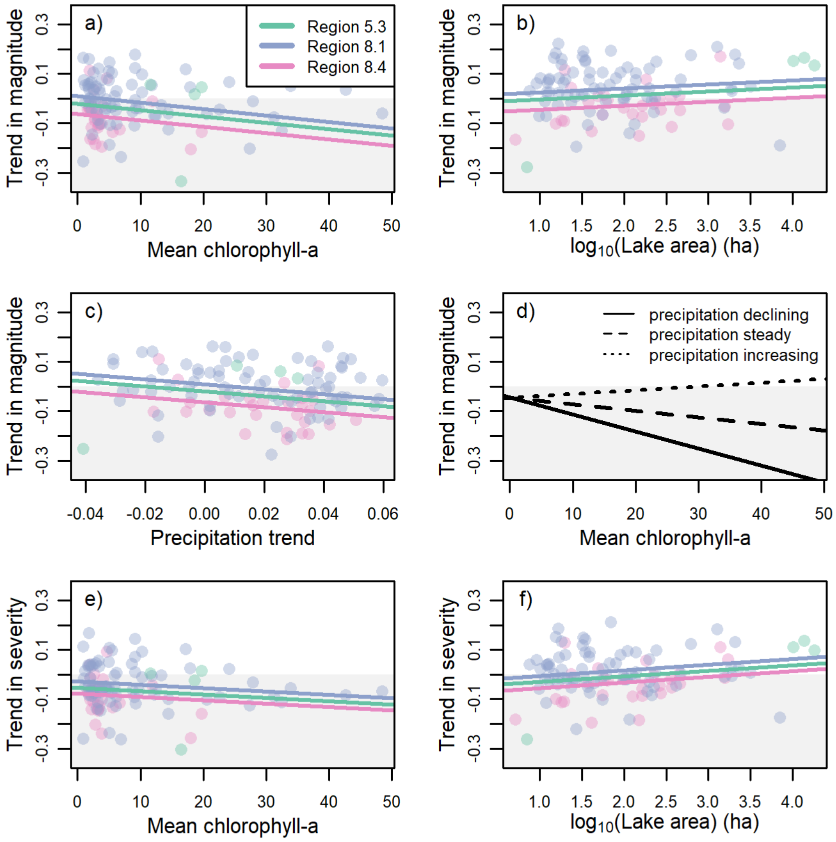


Figure 3. Mixed-model regression effects on trends in bloom magnitude and severity by ecoregion. Residuals have effects of top model predictors not on the x-axis statistically removed. In (d), declining corresponds to a precipitation intensification (95th percentile of daily precipitation) trend of –0.05, steady corresponds to a trend of 0, and increasing corresponds to a trend of 0.05. For simplicity, in (d) the random effect of ecoregion on the intercept is not depicted. In the background of each panel, the gray rectangle is included to visually delineate between positive and negative trends in the bloom metrics.

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WebPanel 1. Methods and analysis

Long-term trends in bloom metrics

We analyzed 323 lake chlorophyll-*a* time-series well-suited to capturing long-term trends in algal blooms; specifically, those that were consistently sampled with high frequency during the summer months over a decade or more. Time-series were obtained from the LAGOS-NE database using the *LAGOSNE* package in R (Stachelek and Oliver 2019); specifically, we used the data packages LAGOS-NE-LIMNO (v1.087.3; Soranno and Cheruvelil 2019) and LAGOS-NE-LOCUS (v1.01; Soranno and Cheruvelil 2017). Data were also acquired from the US Army Corps of Engineers Rock Island District and the Iowa Cooperative Lakes Area Monitoring Project. Additionally, because LAGOS-NE-LIMNO v1.087.3 contains data only through 2013, we extended the lake time-series using publicly available records from the same monitoring programs included in LAGOS-NE. This included data from the Maine Department of Environmental Protection, Minnesota Pollution Control Agency, New York Citizens Statewide Lake Assessment Program, North Temperate Lakes Long Term Ecological Research program, Rhode Island Department of Environmental Management, Vermont Department of Environmental Conservation, and Wisconsin Department of Natural Resources.

To develop time-series for the trend analysis, we first identified lake-year combinations with a mean sampling interval of 17.5 days or finer from May to September. We used a mean sampling interval of 17.5 days as it corresponds to a 14-day sampling interval over 3 months, with one missing observation. Informed by a rarefaction analysis of 31 lake-years of daily algal pigment data during the open water season (WebFigure 1), we determined that this interval best balanced precision of the bloom metrics with the inclusion of a large number of lakes spanning a wide range of characteristics. To perform the rarefaction analysis, we systematically subsampled daily algal pigment time-series to approximate sampling intervals from 2 to 30 days, considering all possible unique ways to regularly sample the time-series at each interval. We considered the root mean squared error as a proportion of the true value to assess the loss of precision associated with increasing sampling intervals (WebFigure 1). Algal pigment data were from experimentally eutrophied lakes (Wilkinson *et al*. 2018), hypereutrophic shallow lakes (Ortiz *et al*. 2019), the North Temperate Lakes Long Term Ecological Research Program (NTL Lead PI *et al*. 2020), and Beaver Creek Reservoir (Buelo and Pace, pers comm). From the lakes with an acceptable sampling frequency, we analyzed time-series for which the suitably sampled lake years spanned ≥10 years, with no gaps longer than 3 years, and with neither the first nor last year separated from the next year by a gap of more than 1 year. Leading or trailing years were at times discarded to obtain a time-series that met these criteria. In total, 323 lakes with time-series lengths ranging from 10 to 42 years were included in the analysis.

To characterize long-term trends in the three bloom metrics (magnitude, severity, and duration), we used chlorophyll-*a* data from the selected lakes to compute annual time-series of the following variables: mean chlorophyll-*a*, 95th percentile of chlorophyll-*a*, and the proportion of observations above a threshold value corresponding to perceived loss in recreational value of the waterbody. Threshold values were region-specific and adapted from Angradi *et al*. (2018), who identified the chlorophyll-*a* concentrations that corresponded to a perceived loss in recreational value, from low to marginal value. The threshold for lakes in "plains" ecoregions had an impairment threshold of approximately 40 $\mu g\ L^{-1}$ chlorophyll-*a*, and lakes in the "mountains and upper Midwest" ecoregions were set at an impairment threshold of approximately 11 $\mu g\ L^{-1}$. Prior to analysis of the trends in the bloom metrics, time-series were scaled to have a mean = 0 and variance = 1. We measured trends in each of these variables by fitting a generalized least-squares linear regression against time, with model error having a first-order autoregressive correlation structure. We also tested whether the interannual pattern of the bloom metrics in each lake was better characterized as a simple nonlinear pattern (eg a peak followed by decline in the indicator) by testing whether the data were better explained (difference in Akaike information criteria, $\Delta AIC < -2$) by a quadratic function (Burnham and Anderson 2002). No lakes fit this criterion.

To evaluate if there was evidence for widespread algal bloom intensification, we characterized the distribution of temporal trend coefficients for each bloom metric. Specifically, we determined the percentage of lakes with positive trends, negative trends, statistically significant positive trends ($\alpha = 0.05$), and statistically significant negative trends ($\alpha = 0.05$) for each of the bloom metrics. Additionally, the number of significant positive trends in bloom metrics were tallied with $\alpha = 0.1$ to compare to a recent global study of bloom intensification (Ho *et al*. 2019). We then tallied across all of the bloom metrics for all of the lakes to identify the population of lakes that were significantly deteriorating (significant positive trend in at least one bloom indicator) and those that were significantly improving (significant negative trend in at least one bloom indicator). We also considered whether time-series length affects the distribution of trend coefficients by considering subgroups of the dataset having different lengths (l): 10 years = l < 15 years, $15 \geq l < 20$, $20 \geq l < 25$, $25 \geq l < 30$, and $30 \geq l < 43$. The conclusion of the fraction of lakes with a positive or negative trend in bloom indicators was similar regardless of time-series length (WebFigure 2).

Effects of lake characteristics

Data for predictor variables were obtained from PRISM (2019) and LAGOS-NE-LIMNO v1.087.3 (Soranno *et al*. 2015, 2017) accessed using the R package *LAGOSNE* (Stachelek and Oliver 2019). The time-averaged molar N:P ratio used all paired warm-season total nitrogen and total phosphorus observations for the lake. Time-averaged chlorophyll-*a* was computed as the mean of all observations used in the bloom indicator trend analyses. Temporal trends in nitrogen and phosphorus were computed using the same data selection criteria and statistical methods as for trends in bloom indicators. The temporal trend in 95th percentile of precipitation was calculated by finding the 95th percentile of daily precipitation during the warm season for each year and regressing against year. The temporal trend in mean maximum temperature was calculated in the same manner, using the mean daily maximum temperature during the warm season for each year as the response variable. As ecoregion 5.2 (Mixed wood shield) was only represented by one lake in the dataset, it was combined with ecoregion 5.3 (Atlantic highlands); in addition, the one lake from ecoregion 8.5 (Mississippi alluvial and southeast coastal plains) was considered with ecoregion 8.4 (Ozark Ouachita-Appalachian forests), and the one lake from ecoregion 9.2 (Temperate prairies) was omitted. Analyses were performed in R version 3.6.2 (R Team 2019) using the R packages *lmerTest*, *reghelper*, and *MuMIn* (Kuznetsova *et al*. 2017; Bartoń 2020; Hughes 2020).

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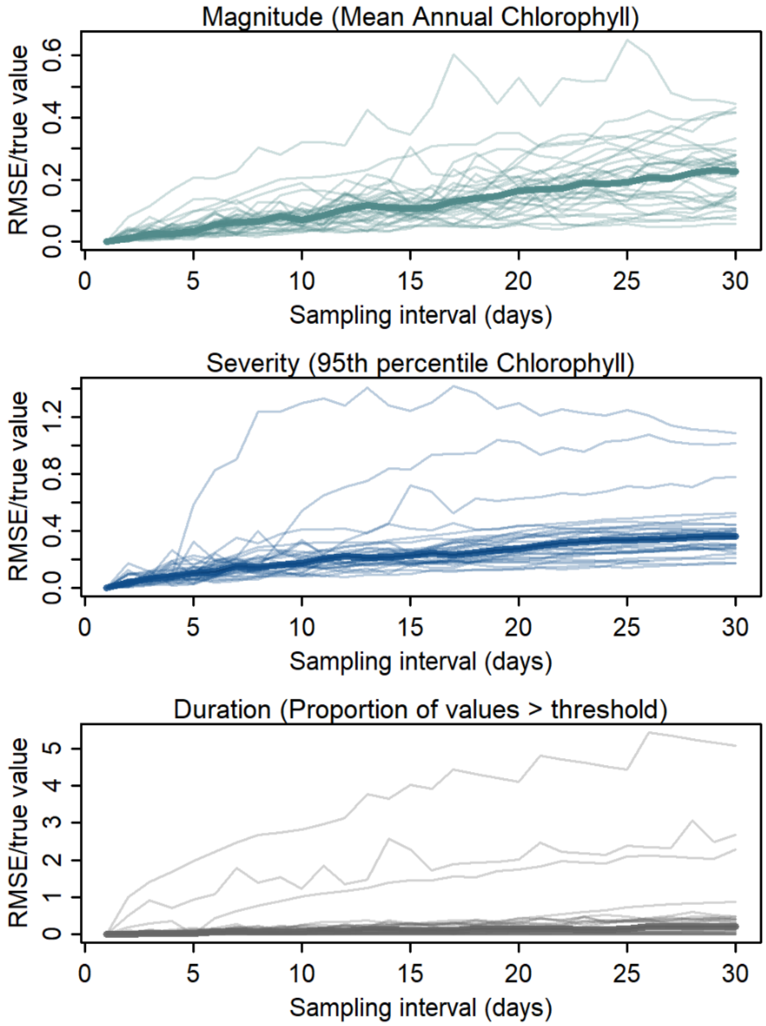

WebFigure 1. Rarefaction analysis was performed on 31 lake-years of daily algal pigment data to evaluate how increasing the interval between sampling events introduces uncertainty in lake algal bloom metrics. The lighter thin lines represent individual lake-years and the solid thick line indicates the median across lake-years. RMSE = root mean squared error.

No evidence of widespread algal bloom intensification in hundreds of lakes

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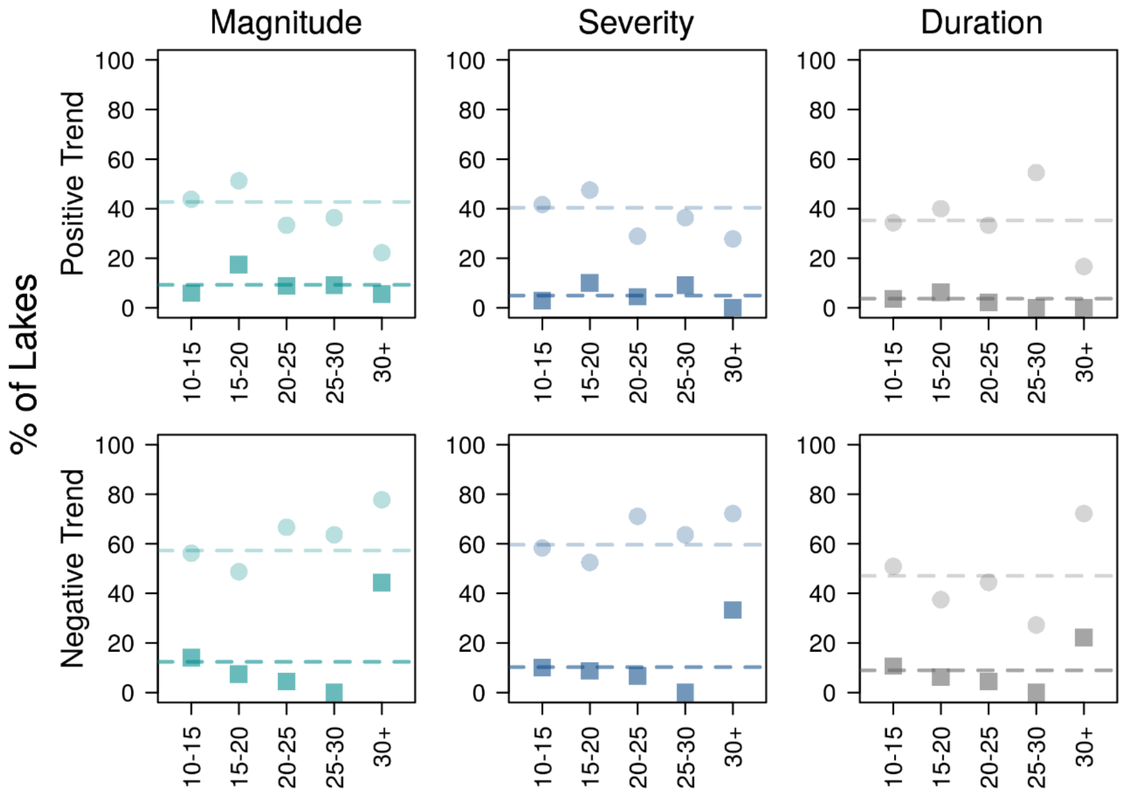
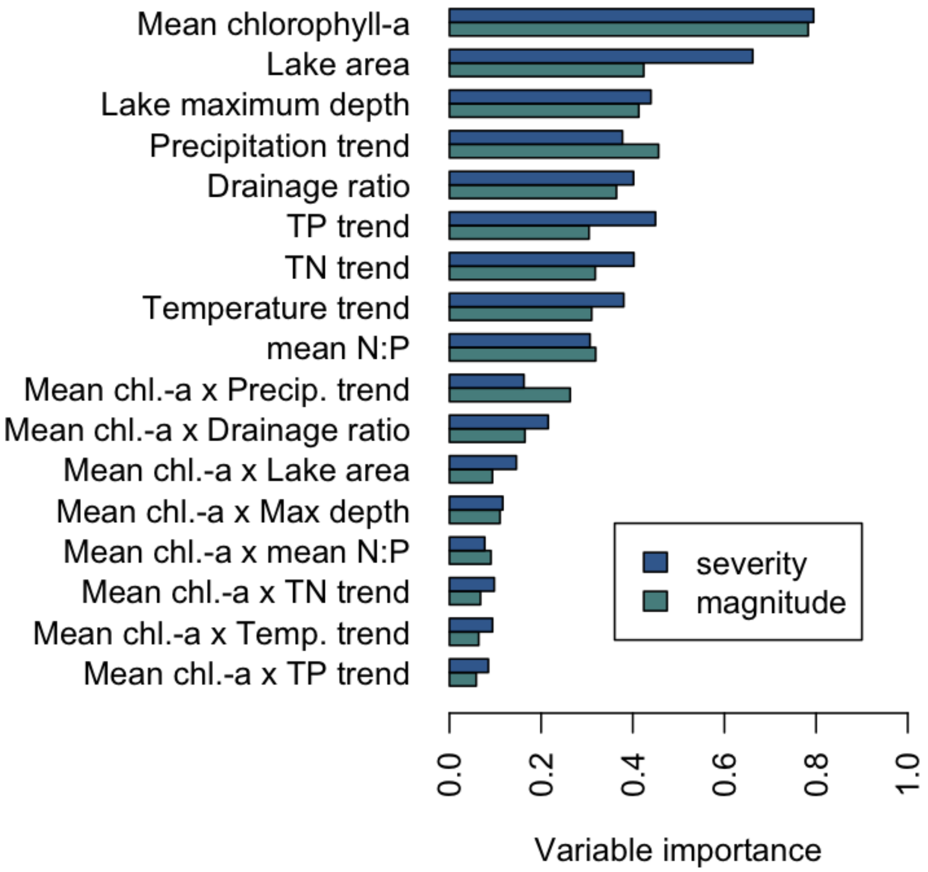


WebFigure 2. Analysis of time series length and the percentage of lakes with positive or negative trends in each of the bloom metrics. The circles are all lakes with a positive or negative trend, whereas the squares are the significant (α=0.05) positive or negative trends. There were 169 lakes with time series lengths of 10-14 years, 80 lakes with 15-20 years, 45 lakes with 21-25 years, 11 lakes with 26-30 years, and 18 lakes with >30 years.



WebFigure 3. Predictor variable importance for response variables severity and magnitude. Variables are ordered by the average of their importance across both response variables. TP = total phosphorus, TN = total nitrogen, chl.-a = chlorophyll-a, N:P = nitrogen to phosphorus ratio, Precip. Trend = temporal trend in the 95% of precipitation, Temp. trend = temporal trend in mean daily maximum temperature.