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The green convergence: United States lakes are collectively moving toward a eutrophic state

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ABSTRACT

Nutrient enrichment and climate change promote algal blooms, leading to many lakes being characterized as eutrophic (i.e., green) worldwide. We examined recent eutrophication trends of freshwater lakes at a national scale by collating 32 years (1990–2021) of growing season (July-September) *in situ* chlorophyll-*a*, nutrient, transparency, and climate data for 1,082 lakes across 32 freshwater ecoregions in the United States. Based on chlorophyll-*a*, 78.2 % (427/546) of lakes initially exhibited eutrophic conditions and have remained eutrophic. Moreover, non-eutrophic lakes converged toward a eutrophic state, with oligotrophic (i.e., clear) or mesotrophic (i.e., moderately clear) lakes becoming greener, and hypereutrophic (i.e., very green) becoming less green. Optimized Hot Spot Analysis suggests lakes in the Appalachian Piedmont and Apalachicola freshwater ecoregions eutrophied more rapidly than other locations. Results suggest nutrient management targeting eutrophic lakes has hindered further degradation, but poor preventative management of clear lakes has led to their eutrophication.

1. Introduction

Cultural eutrophication, the acceleration of nutrient inputs from anthropogenic activities such as agriculture, industrial practices, atmospheric deposition, and sewage, has degraded aquatic ecosystems worldwide since the industrial revolution (Paerl and Huisman, 2008; Taranu et al., 2015). Cultural eutrophication coupled with global climate variations promote freshwater algal blooms (Glibert, 2020; O'Neil et al., 2012; Paerl and Huisman, 2008; Taranu et al., 2015). While algal blooms are a natural phenomenon, some algae can produce toxins that threaten human, livestock, and ecosystem health (Carmichael, 2001). Due to the extensive and potentially severe ecologic, economic and public health impacts related to nutrient enrichment and algal blooms, legislation has been passed in several countries to improve research, monitoring, and management of blooms (Dodds et al., 2009; Hudnell, 2010; Zhou et al., 2017). However, how such management efforts have affected eutrophication, and consequently algal bloom trends, of lakes of various in recent decades at a national level is not well understood. This study examines whether eutrophication has continued to affect freshwater lakes in the contiguous United States (U.S.) since 1990, by considering the initial trophic state of each lake at the beginning of sampling and focusing on the trajectory of eutrophication. Additionally, the study explores how chlorophyll-*a* trends are connected to various lake parameters, such as nutrient concentration, transparency, climate trends and region, freshwater (FW) ecoregion, and surface area.

Eutrophication is determined by various water quality parameters. A common way to classify lakes is through Carlson's Trophic State Index (TSI) (Carlson, 1977; Fernandez-Figueroa et al., 2021; Meyer et al., 2024), which categorizes lakes into four categories (Table 1) based on their algal biomass (measured as chlorophyll-*a*) or potential algal biomass (based on nutrient concentration, or transparency measured as Secchi disk depth). Oligotrophic (TSI <40, clear) lakes have low nutrient concentrations, resulting in low productivity and clear water. Mesotrophic (TSI 41–50) lakes have moderate nutrient and productivity levels. Eutrophic (TSI 51–70, green) lakes are productive and have high chlorophyll-*a*, giving them a green appearance. Hypereutrophic (TSI >70, very green) lakes have an overabundance of nutrients and algae, leading to hypoxic conditions and posing a threat to the health of the ecosystem. Eutrophic lakes tend to remain stable despite a decrease in

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nutrient input due to internal nutrient loading and other feedback mechanisms that maintain high nutrient availability (Jeppesen et al., 2005; Scheffer and van Nes, 2007; Solomon et al., 2015).

Cultural eutrophication is a leading cause of waterbody impairment in the U.S. In 2012, the U.S. Environmental Protection Agency (U.S. EPA) reported 40 % and 35 % of U.S. lakes show excessive levels of phosphorus and nitrogen, respectively (U.S. Environmental Protection Agency, 2016). The U.S. has invested significant money and resources into managing nutrient loading in lakes, particularly those exhibiting eutrophic and hypereutrophic conditions (U.S. Environmental Protection Agency, 2021). Such nutrient management efforts have largely targeted phosphorus, as phosphorus has historically been considered the limiting nutrient of algal bloom species growth when compared to nitrogen (Schindler, 1974; Smith and Schindler, 2009). Moreover, point-sources of phosphorus can be targeted through remediation efforts such as improved wastewater treatment, development of phosphorus-free detergents, and agricultural run-off management. Despite these efforts, low phosphorus (<10 μg/L) lakes in the U.S. are becoming rarer (Stoddard et al., 2016). Nitrogen, however, can be more challenging to manage as it can also enter aquatic systems through atmospheric deposition or groundwater inputs, which cannot be regulated using point-source management techniques (Elser et al., 2009; Paerl et al., 2016). Moreover, national-level annual agricultural phosphorus fertilizer use has remained stable since 1990, whereas nitrogen fertilizer application has continued to increase nationwide (USDA, 2019). There is evidence that phosphorus management has led to recovery from eutrophication in many lakes (Smith and Schindler, 2009), but Quinlan et al. (2021) highlight the difficulties associated with simply decreasing nutrient inputs to manage eutrophication in lakes worldwide. However, others contend that reducing both phosphorus and nitrogen inputs is necessary to prevent algal bloom intensification in lentic systems (Finlay et al., 2013; Paerl et al., 2016).

Previous water quality syntheses have focused on creating databases to study correlations between commonly measured parameters (Filazzola et al., 2020; Quinlan et al., 2021) or the eutrophication trends of large (>100 km^2) (Fang et al., 2022; Ho et al., 2019; Wagner et al., 2008) and/or temperate lakes (Oliver et al., 2017; Taranu et al., 2015; Wilkinson et al., 2021), which respond differently to climate variations and eutrophication than shallow and smaller lakes (Downing et al., 2006; Scheffer and van Nes, 2007) and sub-tropical lakes (Sarmento, 2012), respectively. This study aims to examine recent national-level eutrophication trends of lakes and reservoirs by collating open-source surface water quality data (Table S1) from lakes of various surface areas and FW ecoregions. The outcomes of this study have important implications for enhancing our understanding of the impacts of nutrient management on lake ecosystems and for informing future research efforts.

2. Methods

To explore recent eutrophication trends across a wide geographic region, a 32-year time series (1990–2021) was collated from median growing season (July-September) *in situ* chlorophyll-*a* (μg/L), total nitrogen (TN, μg/L), and total phosphorus concentrations (TP, μg/L), as well as Secchi disk depth (i.e., transparency, m) of 1082 natural lakes and artificial reservoirs throughout 32 FW ecoregions in the contiguous U.S. (Figs. 1-3). All data used in this study were collated from the open-access sources described in Table S1. Data collation was finalized in September 2021, therefore no additional data published after this time were included in this study. Whereas phytoplankton and cyanobacterial biovolume, phytoplankton toxin (i.e., microcystins), and nitrogen and phosphorus forms are important parameters of eutrophication, these data were beyond the scope of this study due to limited availability.

Lakes were included in the study if the lake was sampled: 1) for at least 10 years (Kendall, 1975), 2) had less than a three-year gap between samples for the first 10 years of sampling, and 3) the most recent sample was collected in or after 2016. Long-term consistent sampling was required to ensure the lakes were being sampled regularly, rather than only when visible discoloration and scum was present, or illnesses were reported. Water samples collected before 1990 were not included, as sampling was inconsistent and sporadic before this time. Additionally, chlorophyll-*a* data had to be reported as concentrations based on *in situ* samples, rather than raw fluorescence units or remote sensing chlorophyll estimates. A total of 1082 lakes met such criteria, with an average of 19 (7.0 SD) sample years (Table S2). Fifty-four percent (54 %) of study lakes (585) had *in situ* data from 1990 to 2021. Forty-six percent (46 %) of study lakes ($n = 497$) had *in situ* data for shorter time frames, but still met the three inclusion criteria specified above and were deemed essential to the study as they increased the spatial distribution of the study lakes. Lake surface area ranged from 0.003 to 82,000 km^2 (mean=248.6, S.D. = 3769.9) and lakes were further classified into five lake size categories for statistical analysis (Figure S4) (Kalff, 2001). The five lake size categories were: small (<1 km^2), medium (1–100 km^2), large (101–10,000 km^2), and great lakes (>10,000 km^2). The surface area distribution of the 1082 study lakes was representative of global lake surface area distributions (Downing et al., 2006; Kalff, 2001):

Table 1
Lake eutrophication trends by initial trophic status. Number of lakes classified as each trophic state at the beginning (T0 n) and end (TF n) of the study period (1990–2021), based on chlorophyll (Chl), total phosphorus (TP), total nitrogen (TN), and Secchi disk depth (Secchi) surface samples, and TSI rate of change (Sen's Slope) from year to year, grouped by T0 TSI status. TSI: trophic state index.

	TSI description		TSI status change			Sen's Slope TSI	
T0 TSI status	Variable	Variable range	T0 n	TF n	% Change	Mean (±95 % CI)	*p*-value
Hypereutrophic (very green lake)	Chl	>56 μg/L	66	67	1.5	−0.31 (0.14)	<0.0001
	TP	>96 μg/L	52	38	−26.9	−0.50 (0.13)	<0.0001
	TN	>2940 μg/L	10	2	−80.0	−0.33 (0.20)	0.001
	Secchi	<0.5 m	37	40	8.1	−0.30 (0.11)	<0.0001
Eutrophic (green lake)	Chl	6.41–56 μg/L	546	559	2.4	−0.08 (0.05)	0.0004
	TP	24.1–96 μg/L	204	169	−17.2	−0.28 (0.06)	<0.0001
	TN	740.1–2940 μg/L	215	214	−0.47	−0.10 (0.04)	<0.0001
	Secchi	0.5–2.9 m	262	261	−0.4	−0.04 (0.04)	0.06
Mesotrophic (moderately clear lake)	Chl	2.61–6.4 μg/L	330	312	−5.5	0.11 (0.06)	0.0003
	TP	12.1–24 μg/L	118	154	30.5	−0.06 (0.08)	0.15
	TN	370.1–740 μg/L	136	161	18.38	0.03 (0.05)	0.23
	Secchi	2–3.9 m	105	101	−3.8	0.06 (0.07)	0.05
Oligotrophic (clear lakes)	Chl	≤2.6 μg/L	140	144	2.9	0.23 (0.09)	<0.0001
	TP	≤12 μg/L	109	122	11.9	0.22 (0.09)	<0.0001
	TN	≤370 μg/L	49	33	32.65	0.29 (0.09)	<0.0001
	Secchi	≥4 m	101	103	2	0.02 (0.07)	0.64

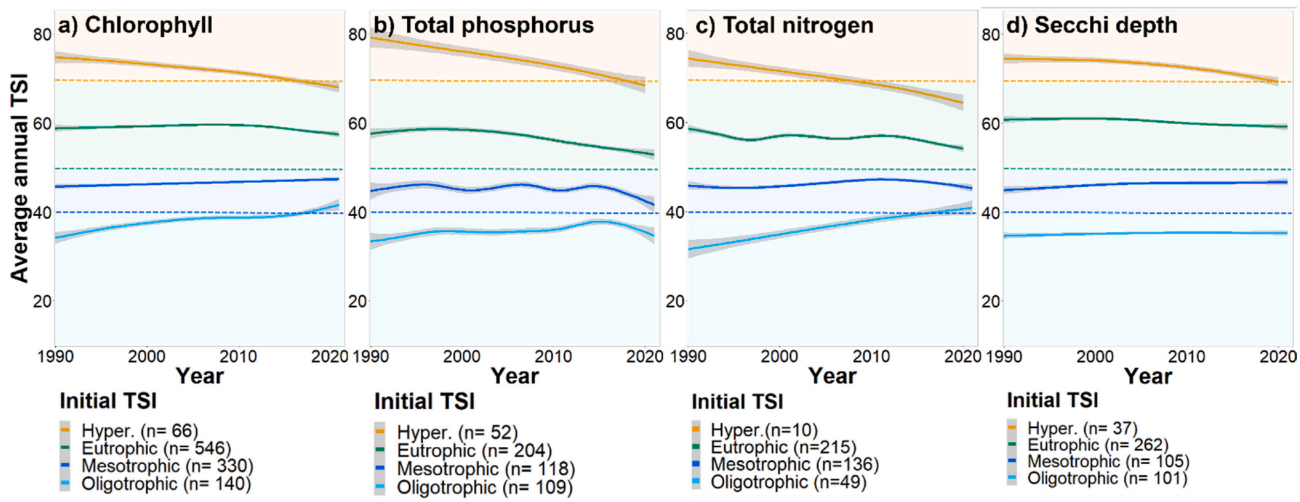

Fig. 1. Average annual median growing season chlorophyll (a), total phosphorus (b), total nitrogen (c), and Secchi depth (d) trophic state index (TSI) values based on surface samples collected from 1082 lakes between 1990 and 2021, grouped by initial (average of first 3 sampling years) TSI status. Dashed horizontal lines indicate TSI value categories: Oligotrophic (clear, TSI 0–40), mesotrophic (moderately clear, TSI 40–50), eutrophic (green, TSI 50–70), hypereutrophic (very green, TSI >70). Gray shading represents 95 % confidence intervals and trends are displayed using LOWESS smoothing.

overwhelmingly skewed towards small (<1 km^2, n = 539) and medium (1–100 km^2, n = 420) sized lakes, with relatively few large (101–10,000 km^2, n = 38) and great lakes (>10,000 km^2, n = 4; Figure S4). Large lakes account for more total surface area, but small and medium lakes are far more abundant in number and spatial range (Downing et al., 2006; Kalff, 2001).

Carlson's TSI values were calculated to standardize and normalize the water quality parameters, which were non-normally distributed and measured in different units, and categorize the lakes based on initial trophic status (T0, average first 3 years of sampling). Chl (1), TP (2), TN (3), and Secchi disk depth (4) measurements were converted to TSI values based on the following formulas(Carlson, 1977; Kratzer and Brezonik, 1981):

(1) Chl TSI = 9.81 ln(Chl) + 30.6
(2) TP TSI = 14.42 ln(TP) + 4.15
(3) TN TSI = 54.45 + 14.43 ln(TN)
(4) Secchi TSI = 60 – 14.41 ln(SD)

where Chl = chlorophyll-a pigment concentration (μg/L), TP = total phosphorus concentration (μg/L), TN = total nitrogen concentration (mg/L), and SD = Secchi disk depth (m).

FW ecoregions were used in this study to identify watershed-level trends, as FW ecoregions largely correspond to major watersheds and are designed to spatially divide areas based on freshwater biodiversity (Abell et al., 2008). FW ecoregion percent land cover calculations were based on 30 m land cover data provided by the North American Land Change Monitoring System (The North American Land Change Monitoring System, 2020). Climate division (n = 138) scale annual mean and maximum growing season (July-September) air temperature (°C), growing season precipitation (mm), and annual drought (Palmer Z Index) data were accessed through the Climate at a Glance National Oceanic and Atmospheric Administration (NOAA) application (NOAA, 2021). Mean and maximum summer air temperature values were used in place of lake surface temperatures, as these values were not available for most lakes and summer air temperatures are a significant predictor of surface water temperatures (O'Reilly et al., 2015).

The Mann-Kendall (M-K) statistics were calculated to test for the presence of monotonic time trends, as this non-parametric test does not require data to be normally distributed and has low sensitivity to missing values (Gilbert, 1987; Kendall, 1975; Mann, 1945). The test provided information about trend direction (M-K S), significance (M-K z, $p < 0.05$), and rate of change (Sen's slope β). When lakes had multiple observations per year, annual growing season medians were calculated and used as the representative annual value, which is standard practice to reduce the effects of autocorrelation and conform to the required single observation per time period for the M-K test (Gilbert, 1987). M-K trend statistics were also generated from 1990 to 2021 growing season climate data (i.e., mean and maximum temperature, precipitation, and drought) for the 183 climate subdivisions in which the lakes were located, to determine if there was a relationship between water quality and climate trends. For climate parameters, the M-K values were calculated based on the average 5-year increments rather than annual median values, to better represent long-term changes in climate rather than modest annual variations. Statistical analyses were executed utilizing the *trend* and *Kendall* packages of R version 4.1.2 (Supplemental Information 1) (McLeod, 2011; Pohlert, 2020; R Core Team, 2021).

Spearman rank correlations were used to determine the relationship between observed water quality and climate trends, as the data were not normally distributed and contained outliers (Schober et al., 2018). The non-parametric Kruskal-Wallis test was used to identify between M-K trend significance classification, initial trophic state, and FW ecoregion differences, as the data were non-normally distributed and contained outliers. Post hoc analysis was conducted using the Dunn test for multiple comparisons, as this test is not sensitive to groups with different numbers of observations (Dunn, 1964).

An *Optimized Hot Spot Analysis* (OHSA) was performed in ArcGIS Pro 2.9 to determine if there were statistically significant clusters of lakes displaying increasing or decreasing median growing season chlorophyll concentrations anywhere across the study area. The OHSA tool uses the Getis-Ord Gi* statistic (Ord and Getis, 1995) to measure spatial autocorrelation between values across space and provides information about if and where high or low values cluster spatially.

3. Results

Results from this study demonstrated that most study lakes remained in, or converged to, a eutrophic (i.e., green) state in the past 32 years. Hypereutrophic and eutrophic lakes were significantly less green, but remained green throughout the study period, whereas oligotrophic and mesotrophic lakes were significantly greener toward the end of the study (Fig. 1, Figure S1, Table 1). Chlorophyll-a trends were closely correlated to phosphorus and nitrogen trends, as well as transparency (i.e., Secchi disk depth) trends (Figure S2, Table 1 and S2). There was no clear relationship between chlorophyll-*a* trends and lake surface area, climate region, climate trends (i.e., precipitation, temperature), or lake impairment status (Supplementary Information Section 2, Figure S4, Tables S2–3).

Lakes that were classified as hypereutrophic at the beginning of the study period (i.e., first three sample years) showed significant decreases in summertime chlorophyll-*a* (Chl TSI, -0.31 ± 0.14 95 % C.I.; $p < 0.0001$; Fig. 1 and Table 1), total phosphorus concentration (TP TSI, -0.50 ± 0.13 95 % C.I., $p < 0.0001$), and total nitrogen concentration (TN TSI, $-0.33 \pm 0.$ 95 % C.I., $p < 0.0001$), while also becoming significantly clearer (Secchi TSI, 0.30 ± 0.11 CI, $p < 0.0001$). Notably, 48.1 % ($n = 25$) of lakes that were initially classified as hypereutrophic based on total phosphorus became eutrophic by the conclusion of the study period. Of those 25 lakes, seven were identified as nutrient impaired in 2002 by the Clean Water Act (CWA) Section 303(d) Program (U.S. Environmental Protection Agency, 2021) (Figure S4). This program identifies systems impaired by pollutants and establishes pollutant Total Maximum Daily Loads values to guide management and monitoring efforts.

Half ($n = 546$) of the study lakes were eutrophic based on chlorophyll-*a* at the beginning of the study period. Eutrophic lakes significantly decreased in chlorophyll-*a* (Chl TSI, -0.08 ± 0.05 95 % C.I.; $p = 0.0004$; Fig. 1 and Table 1), phosphorus concentration (TP TSI, -0.28 ± 0.06 95 % C.I., $p < 0.0001$), and nitrogen concentration (TN TSI, -0.10 ± 0.04 95 % C.I., $p < 0.0001$) by the conclusion of the study period. While the observed decreases were statistically significant, they were generally not sufficient to cause a trophic state shift from green to clear, with 78.2 % of lakes remaining in a eutrophic state based on chlorophyll-*a* throughout the study.

Mesotrophic lakes were significantly greener (Chl TSI, 0.11 ± 0.06 95 % C.I.; $p = 0.0003$; Fig. 1 and Table 1) and marginally more transparent (Secchi TSI, 0.06 ± 0.07 95 % C.I.; $p = 0.05$) at the end of the study. Although phosphorus concentrations have not significantly changed in mesotrophic lakes (TP TSI, -0.06 ± 0.08 95 % C.I.; $p = 0.15$), there is an optimistic decreasing trend after 2015 (Fig. 1).

Lakes initially classified as oligotrophic significantly increased in summertime chlorophyll-*a* (Chl TSI, 0.23 ± 0.09 95 % C.I.; $p < 0.0001$), total phosphorus concentrations (TP TSI, 0.22 ± 0.09 95 % C.I., $p < 0.0001$), and total nitrogen concentrations (TN TSI, 0.29 ± 0.09 95 % C.I., $p < 0.0001$; Fig. 1 and Table 1). Oligotrophic lakes remained clear throughout the study period (Secchi TSI, 0.02 ± 0.07 95 % C.I.; $p = 0.64$), suggesting that increasing productivity and nutrients did not significantly affect transparency.

Chlorophyll-*a* (Chl) trends were significantly correlated with TN (rho $= 0.53$, $p < 0.0001$), TP (rho $= 0.40$, $p < 0.0001$), and TN:TP (*rho* $= -0.13$, $p = 0.007$) trends (Sen's Slope, Table S3). Chlorophyll-*a* was also associated with transparency (Secchi TSI) trends (*rho* $= 0.51$, $p < 0.0001$, Figure S2, Table S2).

Lakes exhibiting significant increasing ($n = 170$, 15.7 %) and decreasing ($n = 129$, 11.9 %) chlorophyll-*a* (Chl TSI) trends were comparable in number and spatial distribution in this study (Fig. 2, Table S2). An Optimized Hot Spot Analysis was utilized to identify clusters of lakes that were largely increasing or decreasing in chlorophyll-*a* (Fig. 3). Lakes within the northern portion of Middle Missouri (ID=15) and Upper Mississippi (ID = 27) were generally decreasing in chlorophyll-*a*. These results agree with findings of static or decreasing trends in north temperate U.S. lakes (Oliver et al., 2017; Wilkinson et al., 2021). Lakes within the Appalachian Piedmont (ID = 2) FW ecoregion, as well as the northern portion of the Apalachicola (ID = 1) and Mobile Bay (ID = 16) FW ecoregions, are not commonly considered high-risk areas for algal blooms. However, we found that most lakes (67 %, $n = 34$) within Appalachian Piedmont are becoming greener, regardless of initial TSI status (Figure S4, Table S4). This suggests that lakes in this area are exhibiting eutrophication trends that should be addressed to prevent further degradation and ultimately trophic state shifts. Notably, arid and semi-arid climate regions, such as the southwest of the United States, were not well-represented in the dataset because monitoring effort duration or frequency did not satisfy the study's criteria.

4. Discussion

Considering the initial trophic state is critical to identify eutrophication trends, as recent (>1980 CE) observations do not provide context of the pre-industrial prevalence of algal blooms in these lakes (Taranu et al., 2015; Waters et al., 2021). This study addresses these research needs by analyzing eutrophication trends in lakes of various surface areas across 32 FW ecoregions in the U.S. based on initial trophic state. Our findings suggest that most lakes exhibited eutrophic conditions at the start of the sampling period (~1990 CE, $n = 546$, 50 %) and have remained eutrophic in recent decades (Fig. 1).

There has been a growing interest in the creation of water quality databases from diverse systems around the world, especially those related to algal blooms (Filazzola et al., 2020; Meyer et al., 2024; Oliver et al., 2017; Quinlan et al., 2021). For example, freshwater lake eutrophication studies conducted at the regional scale based on *in situ* data (Oliver et al., 2017; Taranu et al., 2015; Wilkinson et al., 2021) or global satellite observations of large lakes (Fang et al., 2022; Ho et al., 2019; Topp et al., 2021; Wagner et al., 2008) report decreasing, static, and increasing eutrophication trends. A global 28-year (1984 - 2012) satellite-based study of 71 large lakes (> 100 km^2) found surface algal blooms have become more intense since the 1980's (Ho et al., 2019). Conversely, a satellite-based study of 344 globally-distributed large

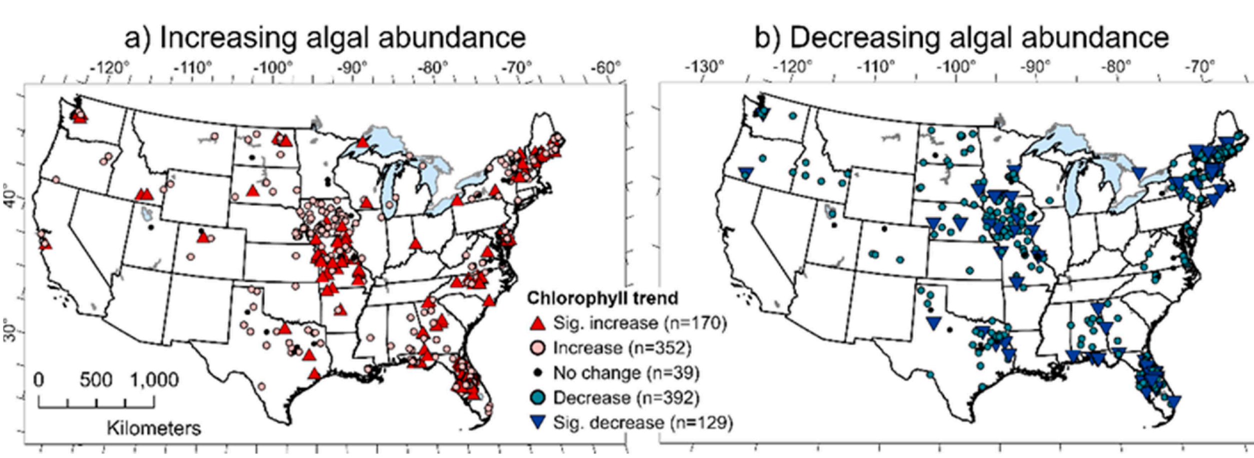

Fig. 2. Spatial distribution of the 1082 study lakes. Fill colors indicate median growing season chlorophyll trophic state index trend significance (M-K z, significance level 0.05) from 1990 to 2021, with lakes showing increasing trends in the left panel (a) and lakes showing decreasing trends in the right panel (b). Sig.: significant.

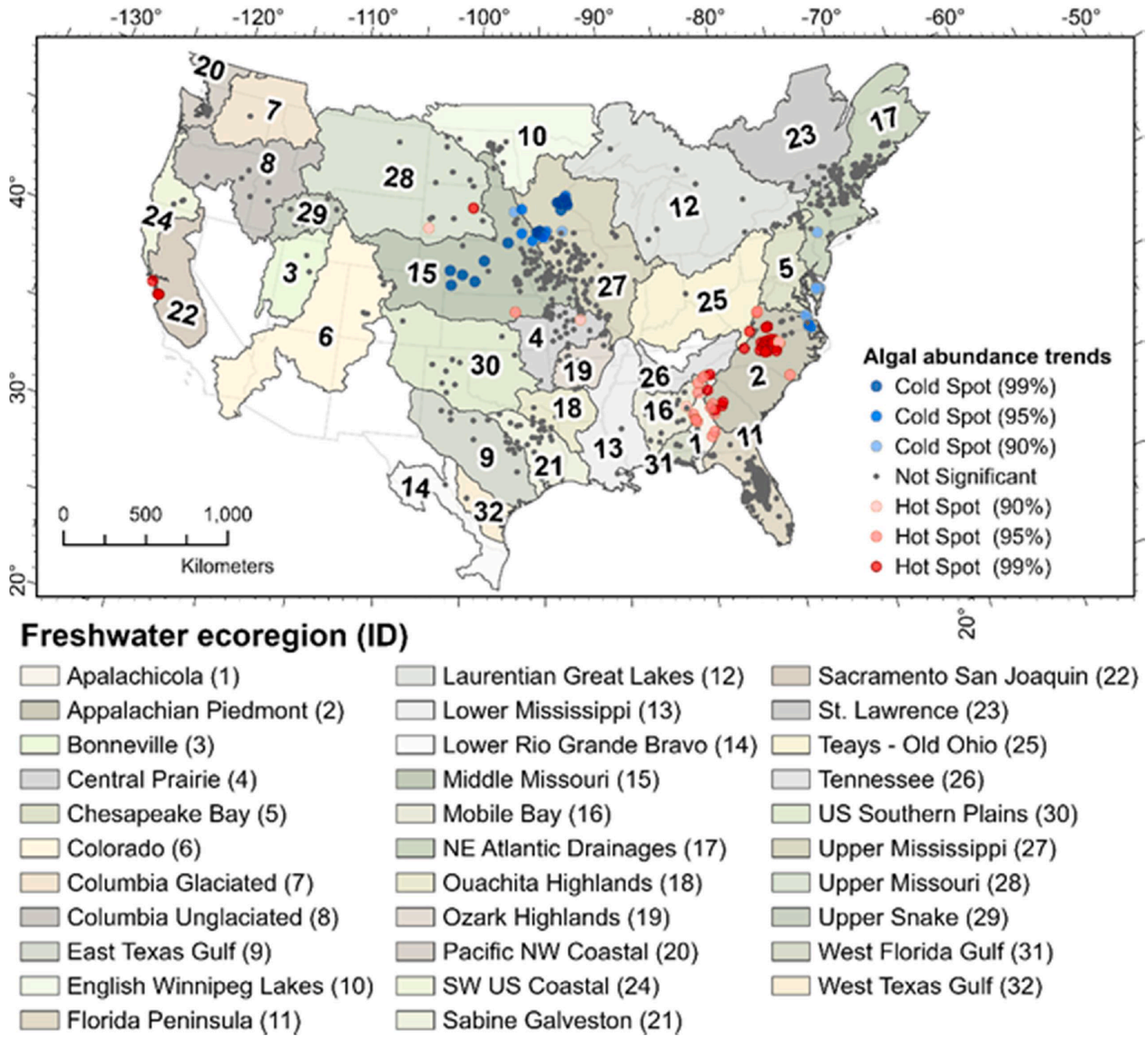

Fig. 3. Clusters of lakes that are increasing (hot spot) and decreasing (cold spot) in growing season chlorophyll-*a*, based on Optimized Hot Spot Analysis, overlaid over freshwater ecoregions (n = 32). Hot and cold spot color gradients represent confidence intervals at 90 % (p = 0.10), 95 % (p = 0.05) and 99 % (p = 0.01), respectively.

lakes found 56 % of lakes show no change in chlorophyll-*a* from 1997 to 2020 (Kraemer et al., 2022). Similarly, regional surveys of 323 temperate lakes in the Northeast and Midwest U.S. (Wilkinson et al., 2021), 527 lakes in the U.S. Rocky Mountains from 1984 to 2020 (Oleksy et al., 2022), and 2913 temperate lakes in the Northeast U.S. from 1990 to 2013 (Oliver et al., 2017) show stable or decreasing chlorophyll, nutrient, or lake color trends. While such reports provide crucial insight of recent lake trophic trends, they often lack initial lake trophic state data, hindering assessment of reported changes and trophic state trajectories. New databases (e.g., Filazzola et al. 2020; Meyer et al. 2024; this study) create exciting opportunities for exploring trends and drivers of water quality changes over time (e.g., Stoddard et al. 2021; Topp et al., 2021).

Lake morphology has been shown to significantly affect how lakes respond and recover from eutrophication and climate variations (Finlay et al., 2013; Scheffer and van Nes, 2007). While lake size can influence multiple drivers of trophic state and algal dynamics, such as internal loading, residence time, and lake turnover, the high variation in small and medium lake size categories was problematic for the analysis conducted in this study. However, it was evident that the systems categorized as great lakes (>10,000 km^2, n = 4) became significantly greener throughout the study period (Figure S4). Finlay et al. (Finlay et al., 2013) noted that systems with high residence times, such as the Great Lakes, promote algal growth through nutrient sequestration thus furthering the importance of dual nutrient management. Additional lake characteristics, such as lake volume, depth, residence time, and lake type (i.e., natural lakes, reservoirs) can also significantly affect algal bloom trends. While large lakes can demonstrate eutrophication heterogeneity (Kutser, 2004), limited sample collection location data (i.e., geographic coordinates) availability or skewed data distributions prevented statistical analysis of the effect of these parameters on the observed eutrophication trends.

Chlorophyll-*a* and transparency were closely related, although brownification likely caused some of the discrepancies observed between TSI values calculated based on chlorophyll-*a* and Secchi disk depth (Figure S2, Table S2) (Leech et al., 2018). Chlorophyll-*a* can affect and be affected by transparency. High chlorophyll-*a* as well as brownification associated with high chromophoric, or colored, dissolved organic matter (CDOM) inputs from terrestrial systems can decrease transparency. CDOM is known to both promote algal growth due to increased nutrient input from run-off, as well as prevent algal proliferation due to reduced light attenuation, oxygen depletion, and decreased mixing depth (Jeppesen et al., 2005; Solomon et al., 2015).

Research and management efforts often focus on eutrophic and hypereutrophic lakes due to the potential ecological, economic, and health risks associated with elevated nutrients and algal blooms (U.S.

Environmental Protection Agency, 2021). Such management efforts appear to have led to the observed decrease in chlorophyll-*a* and phosphorus concentrations of initially eutrophic or hypereutrophic study lakes. However, lake re-oligotrophication was rare, likely due to non-point nutrient sources and internal loading from sediments (Jeppesen et al., 2005; Scheffer and van Nes, 2007; Solomon et al., 2015). Moreover, limited nitrogen management efforts are reflected in the results of this study, with TN values remaining stable in 57 % (n = 235) of study lakes and a similar number of lakes exhibiting significantly increasing (20 %, n = 83) and decreasing (22 %, n = 92) TN trends (Sen's Slope, Table S2).

A decrease in phosphorus, when not accompanied by a reduction in nitrogen, can lead to elevated TN:TP ratios commonly associated with less efficient denitrification processes that may exacerbate nitrogen loading within the system (Elser et al., 2022; Finlay et al., 2013). Potential ecological and management implications of high TN:TP ratios include changes in phytoplankton, and ultimately consumer, growth and diversity (Elser et al., 2022), elevated risk of nitrate polluted drinking water sources, and downstream nitrogen transport to coastal systems (Finlay et al., 2013; Paerl et al., 2016). Most lakes (68 %, n = 274) did not exhibit statistically significant changes in TN:TP, but more lakes were significantly increasing in TN:TP values (22 %, n = 90), than those significantly decreasing (10 %, n = 39, Table S2). Increasing TN:TP trends indicate nitrogen loading is occurring in some study lakes and highlights the importance of researching and implementing dual nutrient management (Finlay et al., 2013; Paerl et al., 2016).

Many of the study lakes that were initially classified as oligotrophic and mesotrophic are experiencing significant increases in chlorophyll-*a* and phosphorus concentrations, potentially due to limited nutrient management efforts being focused on less impaired lakes. Notably, initially oligotrophic lakes such as the Laurentian Great Lakes (>10,000 km^2 surface area) and those within the Appalachian Piedmont and Apalachicola FW ecoregions (Fig. 3, Figure S3-S4) demonstrated concerning increases in growing season chlorophyll-*a*. Increasing algal bloom trends in these FW ecoregions are not reported in other large-scale algal bloom trend studies (Ho et al., 2019; Oliver et al., 2017; Wilkinson et al., 2021), which highlights the importance of considering trends based on initial lake conditions at high spatiotemporal resolutions.

5. Conclusion

This study provides important insights into the eutrophication trends and trajectories of freshwater lakes in the United States over the past three decades by considering the initial trophic state. The results suggest that nutrient management efforts may have prevented further degradation of eutrophic lakes, but limited preventative management may have led to the eutrophication of previously clear lakes. While identification of the specific management strategies or potential regional drivers of the observed trends was beyond the scope of this study, our goal is to provide national scale trends to inform future research that explores the underlying drivers of regional trends. Particularly, identifying the regional drivers of eutrophication observed in Appalachian Piedmont lakes should be prioritized to identify targeted management strategies.

CRediT authorship contribution statement

Edna G. Fernandez-Figueroa: Writing – original draft, Visualization, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Stephanie R. Rogers:** Writing – review & editing, Visualization, Supervision, Project administration, Funding acquisition. **Matthew N. Waters:** Writing – review & editing, Resources, Methodology, Conceptualization. **Alan E. Wilson:** Writing – review & editing, Supervision, Methodology, Funding acquisition, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.hal.2024.102721.

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