Assessing Nutrient Management Strategies to Control Harmful Algal Blooms in Lake Erie

by

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Abstract

Harmful algal blooms (HAB) have impaired Lake Erie's western basin water quality since the 1960s. Drivers of HABs are still the subject of debate and are likely the result of interactions among several biotic and abiotic factors. The problem is twofold: (1) uncertainty in the specific causes of HABs leads to inapt management solutions; and (2) managing a cross-boundary watershed requires collaboration and agreement on apt solutions from multiple stakeholders as well as many U.S. states and Canadian provinces. In this study, we use Bayesian hierarchical modeling (BHM) to investigate the relationships between nitrogen (N) and phosphorus (P) and phytoplankton biomass, cyanobacterial biomass, and microcystin concentration. We used both a within-lake and an across-lake approach and examined whether the inferences from western Lake Erie differ from the ones using multiple lakes across the country. We found that while P is still the primary driver of HABs in Western Lake Erie (WLE), the great variability between stations and months suggests that even within-lake, there may not be a single relationship characterizing phosphorus effects on HABs. We also interviewed 29 stakeholders actively involved in western Lake Erie's watershed. We analyzed the stakeholders' values, attitudes, and policy preferences to understand their differences or similarities and their effects on management decisions. We found that although stakeholders agree on the urgency of the problem, the different opinions and preferences of each interviewee may complicate the decision-making process in a highly collaborative watershed.

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Executive Summary

Lake Erie is a valuable regional resource; it provides $7 billion in associated annual revenue and drinking water to over 11 million people and (US Environmental Protection Agency, 2004). Given the lake's regional significance, it is important to protect it from environmental threats. Yet, harmful algal blooms (HAB) have impaired Lake Erie's western basin water quality since the 1960s, affecting the lake's natural environment and recreation, household use, and fisheries (Kim et al., 2020; Dai et al., 2012). Drivers of HABs are still the subject of debate and are likely the result of interactions among several biotic and abiotic factors. However, scientists agree that eutrophication—excess nutrients in aquatic environments—is a key factor (Heisler et al., 2008), and that anthropogenic activities, particularly agriculture and urban development, contribute to eutrophication (Withers et al., 2014). With HAB events intensifying since the early 2000s, the Great Lakes Water Quality Agreement, first established in 1972, was amended to include a goal to reduce phosphorus loading in Lake Erie by 40% and the implementation of adaptive management (IJC, 2012; Stow et al., 2020). Still, despite ongoing efforts to reduce total P loads in western Lake Erie, HABs continue to jeopardize the region's industries and have the potential to further affect coastal communities' health. The problem is twofold: (1) uncertainty in the specific causes of HABs leads to inapt management solutions; and (2) managing a cross-boundary watershed requires collaboration and agreement on apt solutions from multiple stakeholders as well as many U.S. states and Canadian provinces. To shed light on both aspects, we investigate the role of nutrients—specifically the secondary role of nitrogen—on HABs, as well as factors influencing stakeholder's attitudes and shaping their nutrient management policy preferences.

Though extensive research has established the relationship between high concentrations of P and the occurrence of HABs (Schindler et al., 2016; Fastener et al., 2016), recent work suggests that nitrogen (N) plays a role in the growth and toxicity of cyanobacterial HABs. (Jankowiac et al., 2019; Wagner et al., 2021). In this study, we used Bayesian hierarchical modeling (BHM) to investigate the relationships between N and P and phytoplankton biomass, cyanobacterial biomass, and microcystin concentration. We used both a within-lake and an across-lake approach and examined whether the inferences from western Lake Erie differ from the ones using multiple lakes across the country. Though our findings support the argument that P is still the primary driver of HABs in WLE (Obenour et al., 2014), the great variability between stations and months suggests that even within-lake, there may not be a single relationship characterizing phosphorus effects on HABs. Though the cross-lake models found high effects for nitrogen on HAB size and toxicity while the effect of nitrogen varied greatly within Lake Erie. We found the effect of nitrogen was higher during summer in specific lake stations, consistent with the idea that nitrogen might become the limiting nutrient in certain sites for specific seasons (Chaffin et al., 2013). These findings contribute to the growing evidence suggesting that controlling springtime phosphorus inputs to Lake Erie alone, as stipulated in the

GLWQA (GLWQA Nutrients Annex Subcommittee, 2015), might not be enough to mitigate cyanobacteria bloom size and toxicity throughout WLE in the summer.

In the U.S., state governments are responsible for nutrient management under the GLWQA (Berardo et al., 2019). To date, HAB in Lake Erie has mainly been approached through regulating point source pollution, such as wastewater treatment plants, and through voluntary programs targeting non-point sources. However, this has not led to reduced nutrient levels sufficient to successfully diminish Lake Erie HABs (Wilson et al., 2019). To effectively manage HABs in Lake Erie, a collaborative effort between all stakeholders is necessary. This effort must navigate the variety of stakeholders' views and values and emphasize commitment and compromise from all stakeholders (Rissman and Carpenter, 2015). A better understanding of those stakeholders may engender policies that produce higher collaboration and stakeholder buy-in rates. In this study, we interviewed 29 stakeholders actively involved in the western Lake Erie basin decision-making process. We analyzed stakeholders' values, attitudes, and policy preferences to understand their differences or similarities and their effects on management decisions. Additionally, we used a network analysis to describe the interactions and information exchange among our interviewees' organizations and the larger community around Lake Erie. We found that all interviewees agreed that Lake Erie is vital to the region, that addressing HABs should be a priority, and that state and federal agencies should oversee it. Moreover, we found that a stakeholder's personal values influence their attitudes and policy preferences. Stakeholders that hold different values perceived different barriers for nutrient management and had different preferences regarding voluntary, regulatory, or market-based strategies. We find that although stakeholders agree on the urgency of the problem, the different opinions and preferences of each interviewee may complicate the decision-making process in a highly collaborative watershed.

The Role of Nutrients in Harmful Algal Blooms: A Bayesian Hierarchical Model Comparison of Lake Erie and Across-Lake Inferences

Introduction:

Harmful algal blooms (HABs) have significantly increased in frequency and severity over recent decades, becoming a worldwide environmental problem (Harke et al., 2016; Wilhelm et al., 2020). HABs have been observed in all U.S. states, ranging from freshwater systems to marine coastal areas (Schmale III et al., 2019). HABs can release toxins and otherwise disrupt ecosystem function (Flynn and McGillicuddy, 2018), which can impair human health and livelihoods in nearby coastal communities through impacts on drinking water, recreation, fisheries, and other ecosystem services (Sanseveriono et al., 2016). Drivers of HABs are still the subject of debate and are likely the result of interaction among several biotic and abiotic factors. However, scientists agree that eutrophication—excess nutrients in aquatic environments—is a key one (Heisler et al., 2008), and that anthropogenic activities, particularly agriculture and urban development, contribute to eutrophication (Withers et al., 2014).

In response to the socio-economic and ecological impacts of HABs, the U.S. took aim at reducing eutrophication and mitigating HAB occurrences, starting with the Clean Water Act (CWA) in 1972 (U.S. EPA, 1972). One of the most noteworthy areas impacted by HABs is Lake Erie's western basin, where HABs have threatened water quality since the 1960s. HABs were diminished in the lake until the early 2000s, when they became a problem again, culminating with an episode in 2014 when the city of Toledo (OH) issued a do-not-drink order to its citizens for three days due to high toxin concentrations (Jetoo et al., 2015). In 2012, the U.S. and Canada revised the phosphorus (P) reduction targets established in the Great Lakes Water Quality Agreement (GLWQA) and agreed to a 40% reduction goal in Lake Erie (GLWQA Nutrients Annex Subcommittee, 2015). Despite ongoing efforts to reduce total P loads in western Lake Erie, HABs continue to jeopardize the region's fisheries and tourism, and have the potential to affect community health further.

While extensive research has established the relationship between high concentrations of P and the occurrence of HABs (Schindler et al., 2016; Fastener et al., 2016), recent work suggests that nitrogen (N) plays a role in the growth and toxicity of cyanobacterial HABs. Recent studies

indicate that nitrogen availability affects phytoplankton communities and promotes the prevalence of toxin-producing strains of cyanobacteria, such as *Microcystis* spp., potentially stimulating their growth and toxin production (Jankowiac et al., 2019; Wagner et al., 2021). These strains also appear to be well-adapted to P limitation, indicating that targeting P reduction alone might not prevent HABs (Paerl et al., 2004; Paerl, 2009; Xu et al., 2010; Havens et al., 2015).

Scientists have argued that either P alone or P plus N are the relevant nutrient drivers of HABs; however, the intensity or relevance of these effects are almost always dependent on the environmental context in particular ecosystems. The uncertainty in the role of nitrogen is due to lake local variability as well as study design. Often, across-lake comparisons are used to determine the link between these nutrients and response variables, and to support nutrient management strategies. Deriving nutrient criteria from studies using data collected across large geographical regions (i.e., ecoregions) is a common practice due to data availability and practicality (Huo et al., 2014; Yuan and Pollard, 2017; U.S. EPA, 1998). However, studies comparing across-lakes to within-lake nutrient-biomass relationships show discrepancies between the coefficients found with the different approaches and attribute them to Simpson's Paradox, or the Ecological Fallacy (Qian et al., 2019; Liang et al., 2020). Briefly, the idea is that coefficient values, and even the sign, inferred from across-lakes data do not represent what actually happens in each lake because of local variability and confounding factors not accounted for by models. Where multiple measurements are available within each of several lakes, Qian et al. (2019) suggest using Bayesian hierarchical modeling (BHM) as a way to incorporate local variability in the models while deriving estimates that are not susceptible to this statistical issue. This approach is increasingly common in nutrient-HAB modeling and is used to account for spatial and temporal distribution of data as well as for measurement variability (Malve and Qian, 2006; Gronewold and Borsuk, 2010; Cha and Stow, 2013; Obenour et al., 2014; Yuan and Pollard, 2017; Qian et al., 2019). To date, this approach of comparing within and among-lake relationships has not been extended to understand the combined and separate effects of P and N on HAB biomass and toxicity.

In this study, we used BHM to investigate the relationships between P and N and phytoplankton biomass, cyanobacterial biomass, and microcystin concentration. We used both a within-lake and an across-lake approach and examined whether the inferences from each approach differed. For our within-lake analyses, we used the western Lake Erie monitoring dataset (Burtner et al., 2019; Burtner et al., 2020), a weekly time series of multiple stations. This approach allowed us to quantify seasonal and spatial patterns in the dependence of HABs on P and N within Lake Erie. For our across-lake analyses, we used the National Lakes Assessment (U.S. EPA, 2010; U.S. EPA, 2016-a) dataset, which includes one or two annual measurements recorded during 2007 and 2012, but covers a wide national area.

Methods:

Study System

We used two publicly available datasets for our analyses: the NOAA/CIGLR Western Lake Erie (WLE) monitoring program and the National Lakes Assessments (NLA) from 2007 and 2012 (U.S. EPA). Lake Erie, the 11th largest lake in the world, comprises three basins, with average basin depth ranging from 7.4m (west) to 24m (east). Lake Erie's western basin is characterized by heavy agricultural land use and includes big metropolitan centers such as Detroit, Toledo, and Cleveland. Two of the lake's main inflows are the Detroit and the Maumee rivers, both located in the western basin and contributing to most of the water and a significant part of the nutrients in the lake, respectively (Richards et al. 2009). Lake Erie's western basin has a long history of eutrophication and HABs, leading to the establishment of the WLE monitoring program and periodical water quality assessments. The WLE monitoring program collects information about nutrients as well as chlorophyll, phycocyanin, and microcystin concentrations at weekly or bi-weekly intervals from May to November and includes multiple established stations as pictured in Figure 1. We used data collected between 2012 and 2019 that are available through NOAA's National Centers for Environmental Information data archive (ncei.noaa.gov; Burtner et al., 2019; Burtner et al., 2020). A summary of key variables in the WLE dataset is shown in Table 1.

The National Lakes Assessment is a survey of randomly selected lakes, ponds, and reservoirs in the contiguous U.S., repeated in 2007 and 2012 (epa.gov/national-aquatic-resource-surveys/nla; U.S. EPA, 2010; U.S. EPA, 2016-a). The survey is designed to assess the ecological condition of U.S. freshwater bodies, track large-scale trends in water quality, and document the extent to which they are suitable for purposes under the CWA. The Great Lakes, the Great Salt Lake, commercial treatment or disposal ponds, and ephemeral lakes are not included in the survey. In each iteration of this survey, over a thousand water bodies were sampled once or twice between May and September. While the 2007 survey assessed only lakes larger than 10 acres, the 2012 included lakes larger than 2.47 acres that were at least 1m deep. We used the provided aggregation of Level III ecoregion information, as shown in Figure 1 (Herlihy et al., 2008). A summary of key variables of NLA is shown in Table 2.
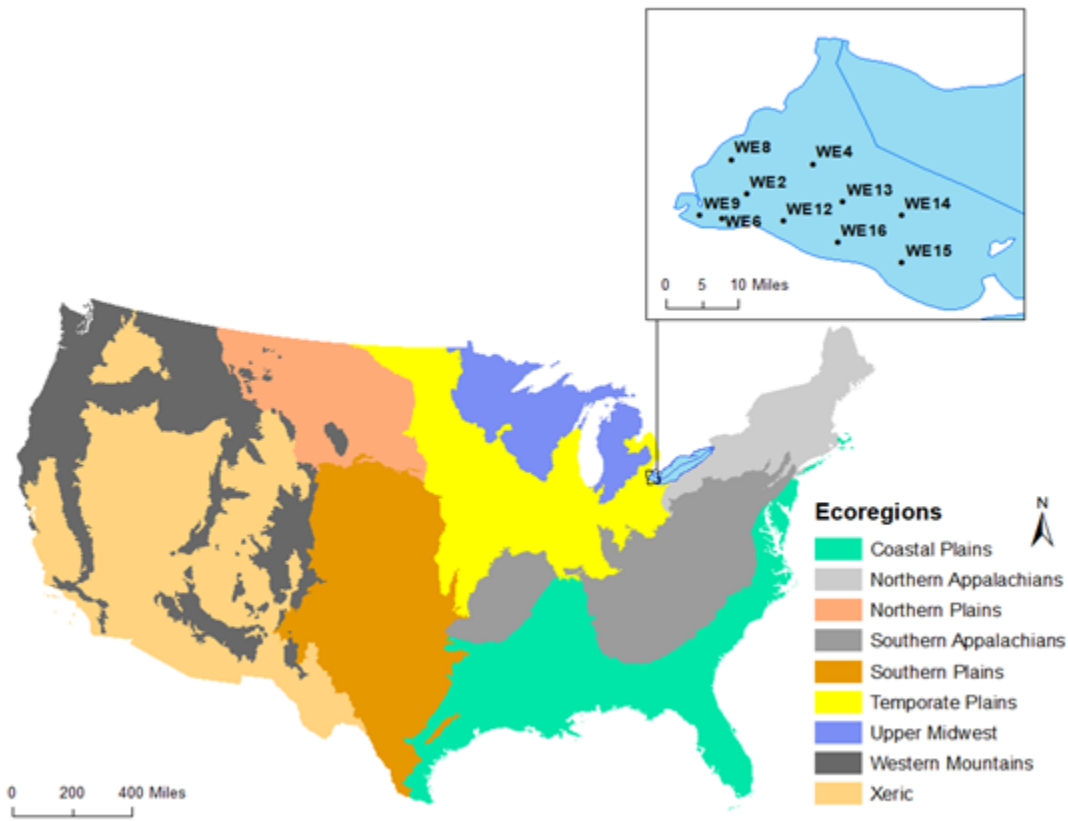
Figure 1. U.S. aggregated ecoregions with Western Lake Erie inset showing ecoregions boundaries and WLE stations location.

Table 1. Summary statistics of key variables across the 853 observations in Western Lake Erie.

	Variable	Min	Max	Mean	Median	n, Total	n, above detection limit
Response Variables	Chlorophyll-a (μg/l)	0.71	6.8×10^3	39.21	16.38	853	853
	Phycocyanin (μg/l)	0.01	8.2×10^3	32.92	3.63	853	834
	Microcystin (μg/l)	0.11	297.5	2.54	0.44	853	570
Predictors	Total P (μg/l)	4.00	2.5×10^3	76.50	49.35	853	853
	Total N (mg/l)	0.10	40.96	1.37	0.71	853	853
Covariates	Temperature (℃)	7.40	29.70	22.14	22.90	853	853
	Conductivity (μs/cm)	1.50	583.3	294.1	279.5	853	853

Table 2. Summary statistics of key variables across the 1832 observations in National Lakes Assessment.

	Variable	Min	Max	Mean	Median	n, Total	n, above detection limit
Response Variables	Chlorophyll-a (μg/l)	0.07	936.0	30.73	8.48	1832	1832
	Cyano-biovolume (μm^3/ml)	12.00	4.3×10^8	5.0×10^6	3.2×10^5	1832	1832
	Microcystin (μg/l)	0.02	78.00	0.72	0.10	1832	710
Predictors	Total P (μg/l)	1.00	4.9×10^3	123.0	37.50	1832	1803
	Total N (mg/l)	0.01	54.00	1.19	0.64	1832	1831
Covariates	Temperature (℃)	9.33	35.50	23.90	24.30	1832	1832
	Conductivity (μs/cm)	2.82	6.5×10^5	667.6	241.8	1832	1832

Statistical Models

While both datasets provide similar information, the WLE monitoring program does not routinely measure total nitrogen and total microcystin concentrations. We calculated these variables at the onset to make our models of different datasets more comparable. To obtain an approximation of total nitrogen (TN) in that dataset, we added the concentrations of ammonium, nitrate, nitrite, and particulate organic N. This estimate of TN does not include any dissolved organic N present, but includes much of the bioavailable N. Similarly, to obtain concentrations of microcystin, we added particulate and dissolved microcystin concentrations. Missing values observations were omitted from the model. Where no estimate was provided for the below detection observations, we assigned them the detection limit value. However, in instances where estimates below detection were given, we kept the original values. The number of below-detection observations for explanatory variables was minimal (<2.2%, Tables 1 and 2) and we believe these do not significantly influence final models. Additionally, we used extracted phycocyanin concentration as an estimate of cyanobacteria biomass.

Because the NLA includes ponds and smaller reservoirs in its survey, we first filtered the data for water bodies that are both deeper than 1 m and present year-round. We used cyano-biovolume as an indicator of cyanobacteria biomass and calculated it as the sum of biovolumes for all Cyanophyta taxa. For consistency, we averaged temperature measurements of the first meter of the water column. We omitted missing observations and replaced negative values with detection limits values. Prior to building the models, we log-transformed data for chlorophyll-a, phycocyanin, cyano-biovolume, TN, TP, and conductivity, as well as standardized temperature and latitude values in both datasets.

 We opted to use microcystin as a categorical variable due to the large number of observations below detection (see Tables 1 and 2). We created two new binary variables using the U.S. EPA's 2015 Health Advisory thresholds for microcystin, 0.3 µg/l and 1.6 µg/l (U.S. EPA, 2015). Water with microcystin concentrations higher than 0.3 µg/l is considered unsuitable for small children to drink while concentrations above 1.6 µg/l are unsuitable for anyone to drink. We performed data analysis in R (R Core Team, 2020).

Model building and selection

We started our analysis by developing the hypothesized relationships between explanatory and response variables, as shown in Figure 2. These relationships were developed from existing literature that quantified those links in observational or experimental studies. We used the 'brms' package in R (Bürkner, 2017; Bürkner, 2018) to create Bayesian hierarchical regressions for each response variable in each dataset, for 8 models in total. To account for the variability among and between ecoregions and WLE stations as well as seasons, we used ecoregion, station, and month

as grouping factors acting on both the intercepts and slopes. Additionally, because initial data assessment revealed TP and TN were relatively strongly correlated, we included a mediation term (P~N) repeated in all models. The median mediation coefficients were 0.53 for WLE and 0.49 for NLA (R^2 = 0.75 and 0.67 respectively). We used these coefficients throughout the rest of the analysis to estimate the effects of nitrogen and phosphorus.

We fitted the models using a Hamiltonian Monte Carlo algorithm. Model fitting was performed in Stan (Stan Development Team, 2020), and the code was compiled using the 'brms' package (Bürkner, 2017; Bürkner, 2018) in R. For all models, we used four chains of 7000 iterations and discarded 3000 for warm-ups. Except for microcystin models, we determined minimally informative priors (normal with a mean of 0 and standard deviation of 5) and used the Gaussian link function. For the logistic microcystin models, we used the Bernoulli family. Additionally, we used the leave-one-out cross-validation method (loo_compare function in 'brms' package, Bürkner, 2017; Bürkner, 2018) to compare the fit of different models and to aid in deciding between them (Vehtari et al., 2020). When the difference in expected log predictive density between models was small (i.e., comparable to the standard error of the difference), we chose the simpler model. We avoided models that had a high proportion of observations with highly influential data points (Pareto k>0.7). The final model formulas are described in Table 3. All estimates are the mean of the posterior distributions, and the credible interval is the 95% quantiles.

(a)

(b)
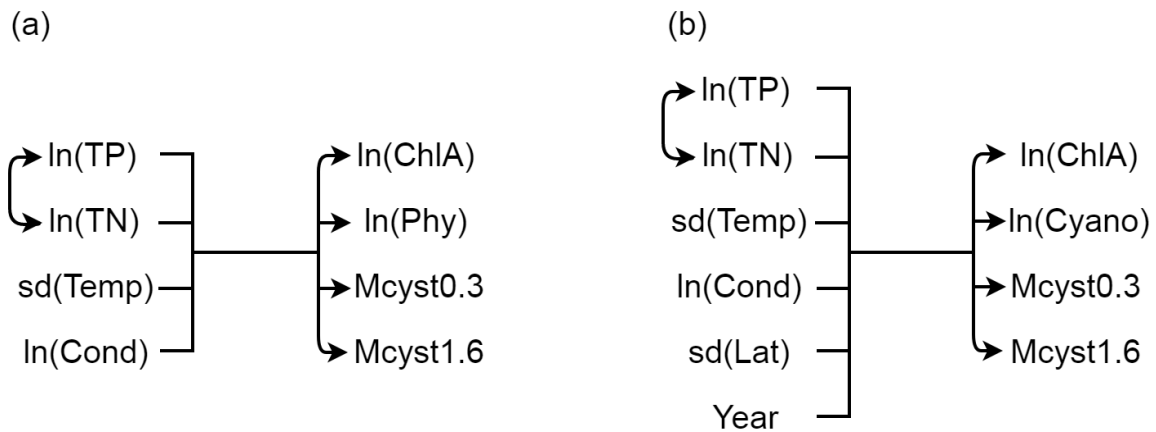
Figure 2. Path diagrams illustrating theoretical relationships among the variables for the a) WLE and b) NLA datasets. In the initial models, these relationships were allowed to vary within each station, month and year (WLE) and within each ecoregion (NLA), and we subsequently simplified those based on model performance until a minimum adequate model. TP represents total phosphorus concentration (μg/l); TN represents total nitrogen concentrations (mg/l); Temp represents water temperature (℃); Cond represents conductivity(μs/cm); ChlA represents chlorophyll-a concentration (μg/l); Phy represents phycocyanin concentration (μg/l); Cyano represents represents cyano-biovolume (μm³/ml); Mcyst0.3 and Mcyst1.6 represent the 0.3 and 1.6 μg/l thresholds of microcystin concentration. ln() indicates natural log transform and sd() indicates standardize transform. The same abbreviations are used in Table 3.

Effects of N and P

By adding the mediation term in our models, we estimate an indirect effect in addition to a direct effect of P on the response variables. We calculate the total effect of P as follows: $\beta_{P,total} = \beta_{P,direct} + \beta_N \times \beta_{N\_P} + \rho_{N,N\_P} \times \sigma_N \times \sigma_{N\_P}$. Where the total effect of P ($\beta_{P,total}$) is the sum of the direct effect of P ($\beta_{P,direct}$) and the indirect effect of P, calculated as the product of nitrogen coefficient (β_N) and the mediation coefficient (β_{N_P}) added to the product of the correlation of N and the mediation coefficient (ρ_{N,N_P}) to the standard deviation of these two parameters (σ_N and σ_{N_P}). The mean of the posterior draws is presented as the effect estimate, and the 95% quantiles are the credible interval.

Finally, we used the hypothesis testing function (hypothesis in package 'brms', Bürkner, 2017; Bürkner, 2018) to obtain the evidence ratios (ER) for our inferences. For coefficients with a positive mean, the ER is the number of posterior draws that are positive to those that are negative or zero. We did not apply any arbitrary cutoffs to the ER, but instead present these along with a qualitative statement on the strength of support.

Table 3. Final model for each response variable. Coefficients and intercepts are not included in the formulas. The equation notation follows that used in Ho and Michalak (2020) and the 'lme4' R package for mixed effects models.

Dataset	Response Variable	Final Model Formula
WLE	ln(TN)	ln(TP)+ (1+ln(TP)| Year)+ (1+ln(TP)| Month)+ (1+ln(TP)| Station)
	ln(ChlA)	ln(TP)+ ln(TN)+ sd(Temp)+ ln(Cond)+ (1+ln(TP)+ ln(TN)+ sd(Temp)+ ln(Cond)| Year)+ (1+ln(TP)+ ln(TN)| Month)+ (1+ln(TP)+ ln(TN)+ln(Cond)| Station)
	ln(Phy)	ln(TP)+ ln(TN)+ sd(Temp)+ ln(Cond)+ (1+ln(TP)+ ln(TN)+ sd(Temp)+ ln(Cond)| Year)+ (1+ ln(TN)+ ln(Cond)| Month)+ (1+ln(TP)+ ln(TN)| Station)
	Mcyst0.3	ln(TP)+ ln(TN)+ sd(Temp)+ ln(Cond)+ (1+ln(TP)+ ln(TN)+ sd(Temp)+ ln(Cond)| Year)+ (1+ ln(TP)+ ln(TN)+ ln(Cond)| Month)+ (1+ln(TP)+ ln(TN)| Station)
	Mcyst1.6	ln(TP)+ ln(TN)+ sd(Temp)+ ln(Cond)+ (1+ln(TP)+ ln(TN)+ sd(Temp)+ ln(Cond)| Year)+ (1+ ln(TP)+ ln(TN)+ ln(Cond)| Month)+ (1+ln(TP)+ ln(TN)| Station)
NLA	ln(TN)	ln(TP) + (1 + ln(TP)| Ecoregion)
	ln(ChlA)	ln(TP)+ ln(TN)+ sd(Temp)+ ln(Cond)+ sd(Lat)+ Year+ (1+ ln(TP)+ ln(TN)+ sd(Temp)+ ln(Cond)+ sd(Lat)| Ecoregion)+ (1| Lake)
	ln(Cyano)	ln(TP)+ ln(TN)+ sd(Temp)+ ln(Cond)+ sd(Lat)+ Year+ (1+ ln(TP)+ ln(TN)+ sd(Temp)+ ln(Cond)+ sd(Lat)| Ecoregion)+ (1| Lake)
	Mcyst0.3	ln(TP)+ ln(TN)+ sd(Temp)+ ln(Cond)+ sd(Lat)+ Year+ (1+ ln(TP)+ ln(TN)+ sd(Temp)+ ln(Cond)+ sd(Lat)| Ecoregion)+ (1| Lake)
	Mcyst1.6	ln(TP)+ ln(TN)+ sd(Temp)+ ln(Cond)+ sd(Lat)+ Year+ (1+ ln(TP)+ ln(TN)+ sd(Temp)+ ln(Cond)+ sd(Lat)| Ecoregion)+ (1| Lake)

Results and Discussions:

Chlorophyll-a

Based on previous studies (Chaffin et al., 2018; Phillis et al., 2008; Kim et al., 2020), we expected to find positive coefficients for both total P and N concentrations in our chlorophyll-a models. Figures 3c and 3d show that for the WLE dataset the coefficient for total effect of P on chlorophyll-a was 0.66, and the coefficient for total N was 0.16 (ER = 726.27 and 3.58). In the NLA models, the coefficient for total effect of P was 0.78 and for nitrogen was 0.76 (ER => 16,000) (Fig. 3e and 3f). Overall, phosphorus coefficients had a narrower CI for all WLE stations and ecoregions when compared to nitrogen coefficients (Fig. 3). For both nutrients, population-level CIs were narrower for NLA than WLE (Fig. 3). Seasonality plays an important role in Lake Erie and the coefficients for both P and N were larger for the summer bloom-prone months as compared to the overall population level effects (ER = 17.82 and 19.30) (Fig. 3c and 3d). The effect of P and N was higher for stations WE4 and WE15. Those two stations are further away from the Maumee River than the others and generally have lower nutrients, suggesting that nutrient dependence is strongest at the edges of the region of river influence. This is consistent with past work showing that loadings of P, in particular, are a strong predictor of the maximum area covered by the bloom (Stumpf et al., 2012). For NLA, the effect of phosphorus was higher for ecoregion UMW (upper midwest), which is also where the effect of nitrogen is one of the lowest. We believe this could be due to the high N:P ratio in this ecoregion, indicative of P-limited growth of phytoplankton in lakes (Paerl et al., 2016). This nutrient imbalance could be a consequence of management policies solely targeting P load reduction from agricultural land in the area, resulting in higher N:P ratios and consequential P limitation (U.S. EPA, 2016-b; Chitikela et al., 2017).
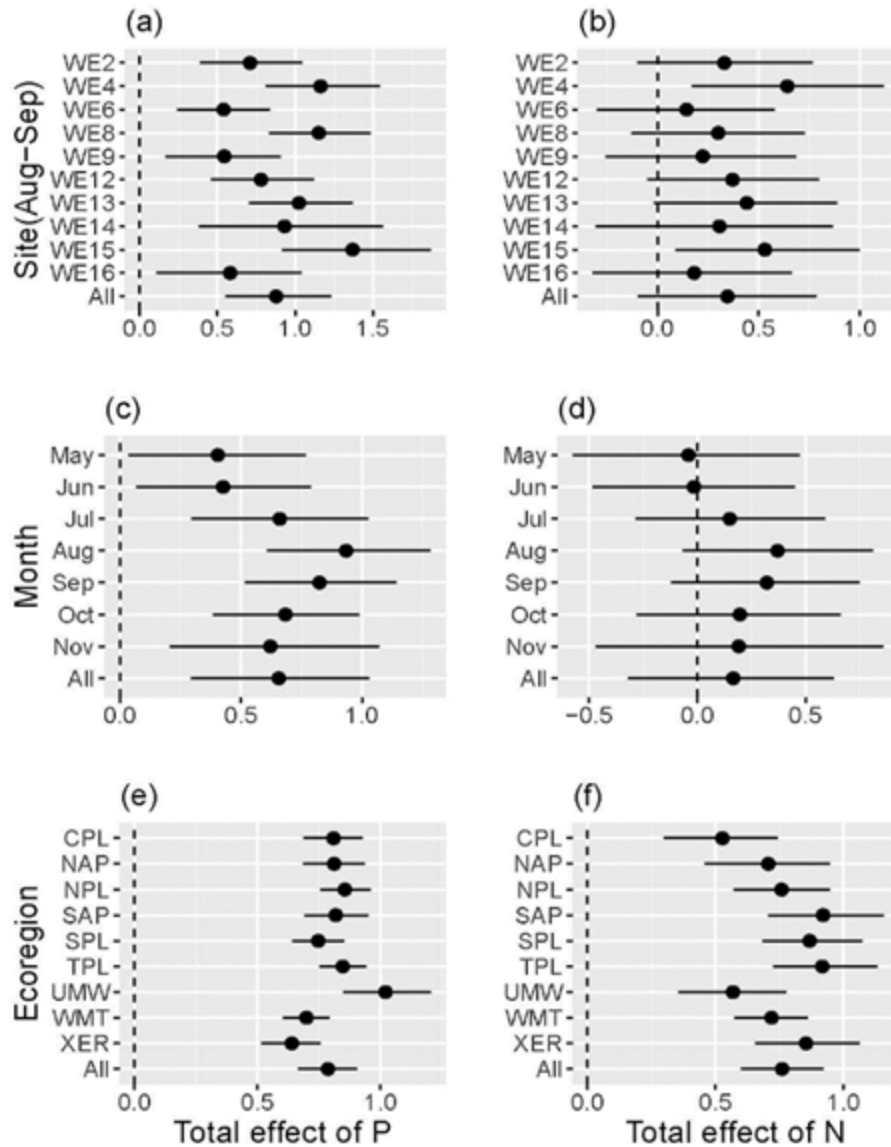
Figure 3. Forest plots for total effect of P and N on chlorophyll-a. a) Forest plot for total effect of P in WLE by stations in August and September; b) Forest plot for total effect of N in WLE by stations in August and September; c) Forest plot for total effect of P in WLE by months; d) Forest plot for total effect of N in WLE by months; e) Forest plot for total effect of P in NLA by ecoregions; f) Forest plot for total effect of N in NLA by ecoregions. The estimated R^2 for the chlorophyll-a models was 0.69 and 0.83 for WLE and NLA, respectively.

Cyanobacteria biomass

As hypothesized, the coefficients of P and N for both cyano-biomass variables were positive, though they varied greatly between datasets and among levels within each dataset (Fig. 4). For both models (phycocyanin in WLE and cyano-biovolume in NLA), we found strong support for the positive total effect of P (399 and ER > 26,000 respectively) (Fig. 4a and 4e). High

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coefficients indicate that P is a strong predictor of cyanobacteria biomass across WLE stations and ecoregions, particularly during the summer months (Fig. 4c). Like the chlorophyll-a models, the coefficients of P were higher for WLE stations 4 and 15 and for the NLA in the UMW ecoregion. Regarding N, we found strong support for the estimated effect in the NLA model, with N being a strong predictor for cyanobacterial biomass (coef.=0.9, ER > 27,999.). For the WLE phycocyanin model, we did not find strong support for the population-level effect of nitrogen (ER = 3.11). However, coefficients for summer months (0.63) and stations 4 and 15 (1.18 and 0.89) showed a stronger effect of total nitrogen on cyanobacteria biomass and had stronger support (all had ER > 5) (Fig. 4b and 4d). This means that N concentration is not a strong control on cyanobacteria in the western part of the lake when inorganic N is high, but it may become impactful later during the bloom when inorganic N is low. This is consistent with previous studies showing that in low-flow years, HAB growth shifted from P-limited to N-limited growth during summer months (Chaffin et al., 2014).
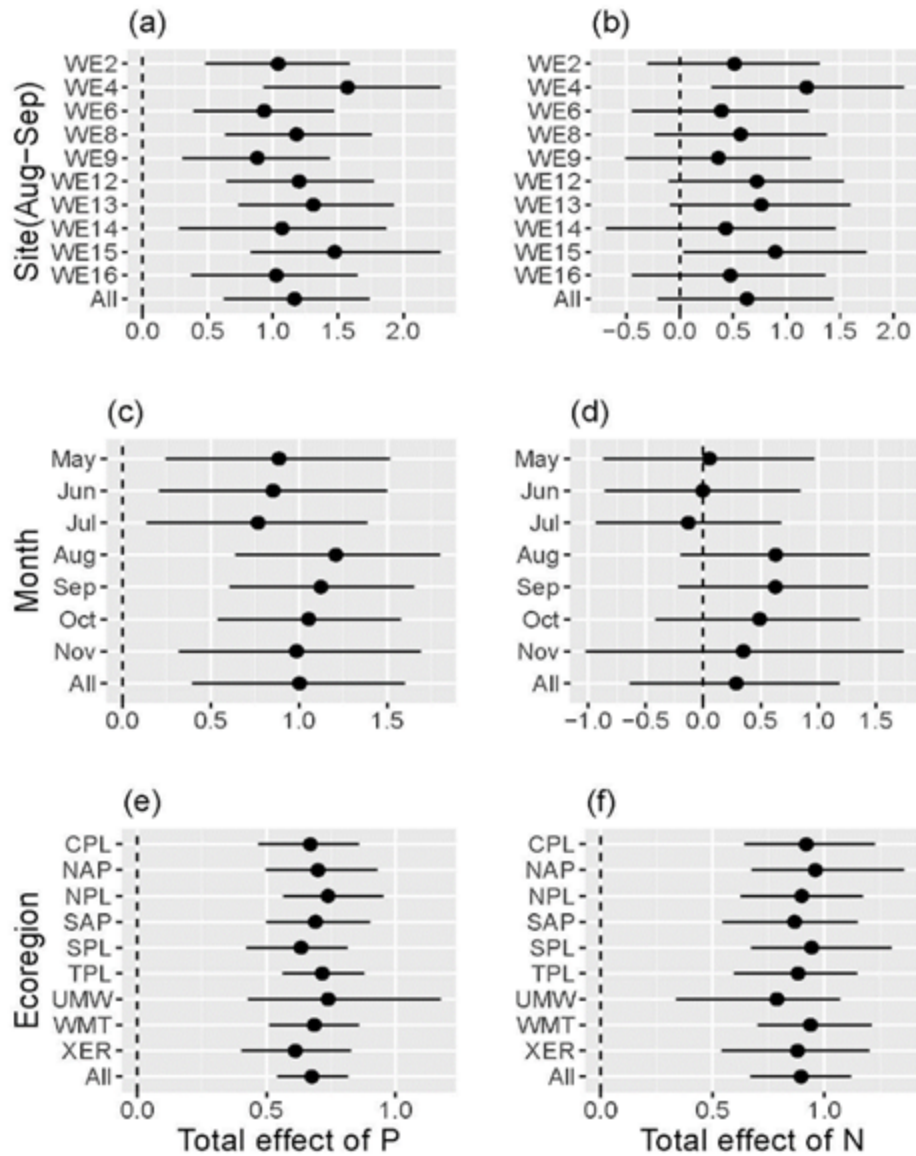
Figure 4. Forest plot for total effect of P and N on phycocyanin and cyanobacterial biovolume. a) Forest plot for total effect of P in WLE by stations in August and September; b)Forest plot for total effect of N in WLE by stations in August and September; c) Forest plot for total effect of P in WLE by months; d) Forest plot for total effect of N in WLE by months; e) Forest plot for total effect of P in NLA by ecoregions; f) Forest plot for total effect of N in NLA by ecoregions. R^2 for the NLA and WLE models was 0.46 and 0.69, respectively.

Microcystin

In all four models of microcystin, phosphorus was a strong predictor of the likelihood that toxin concentration exceeded the threshold, with population-level effects in the logistic regression coefficient ranging from 1.02 to 1.27, and ER >36 for WLE and > 379 for NLA models. Coefficients were relatively homogeneous across WLE stations and NLA ecoregions as seen in

Figure 5, and higher for models describing exceedance of the 1.6 µg/l threshold. Nitrogen coefficients in microcystin models diverged greatly between WLE and NLA models. In both NLA models, coefficients suggest that nitrogen is a strong predictor of toxin concentrations surpassing the thresholds (1.5 and 2.42 for 0.3 and 1.6 µg/l, and ER = inf.). For WLE, models for 0.3 and 1.6 µg/l yield different results. Based on previous studies in Lake Erie (Gobler et al., 2016), we hypothesized the coefficients of nitrogen to be positive. However, the effect of nitrogen on toxin concentration was not strongly greater than zero, and in the spring months, it was negative. Similarly, coefficients for different months and stations all had very weak evidence support (ER < 5). Detecting these seasonal patterns is difficult, owing to the low concentrations of microcystin prior to June. However, we found supportive evidence for a positive effect of nitrogen on toxin concentrations surpassing the 1.6 µg/l threshold when considering August and September at specific stations (Fig. 6a and 6b). ER of nitrogen coefficients > 0 for August, September, and October were 5.7, 8.6, and 14.6, respectively. Moreover, ER of nitrogen coefficients for stations 4, 13, and 15 during these months were 13.57, 13.90, and 6.90, respectively. This suggests that N may not exert control over microcystin concentrations near the mouth of the Maumee River, where inorganic N is typically high. Nevertheless, it can be an important control when inorganic N becomes low during peak bloom at more distant stations.
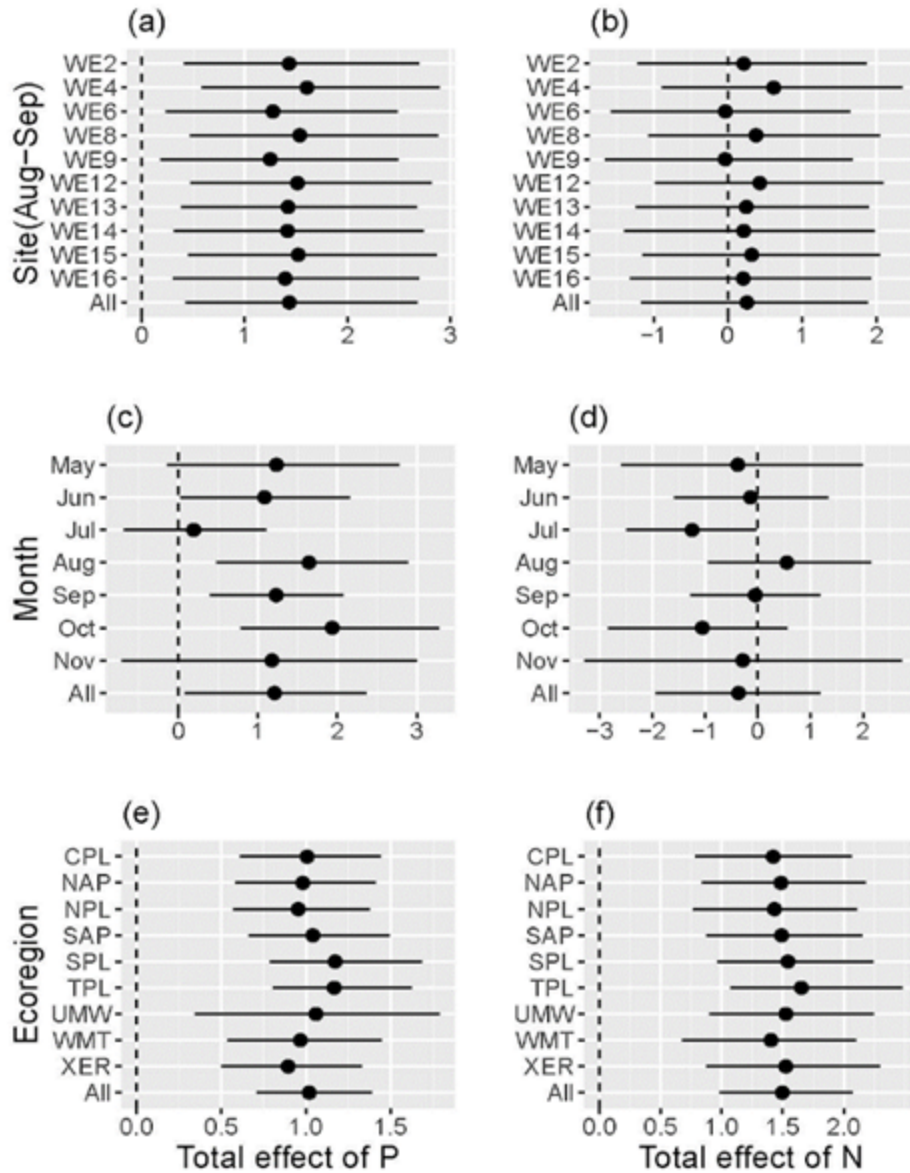
Figure 5. Forest plot for total effect of P and N on microcystin 0.3 µg/l threshold. a) Forest plot for total effect of P in WLE by stations in August and September; b) Forest plot for total effect of N in WLE by stations in August and September; c) Forest plot for total effect of P in WLE by months; d) Forest plot for total effect of N in WLE by months; e) Forest plot for total effect of P in NLA by ecoregions; f) Forest plot for total effect of N in NLA by ecoregions. R^2 for microcystin models were: NLA 0.3 = 0.49, WLE 0.3 = 0.50.

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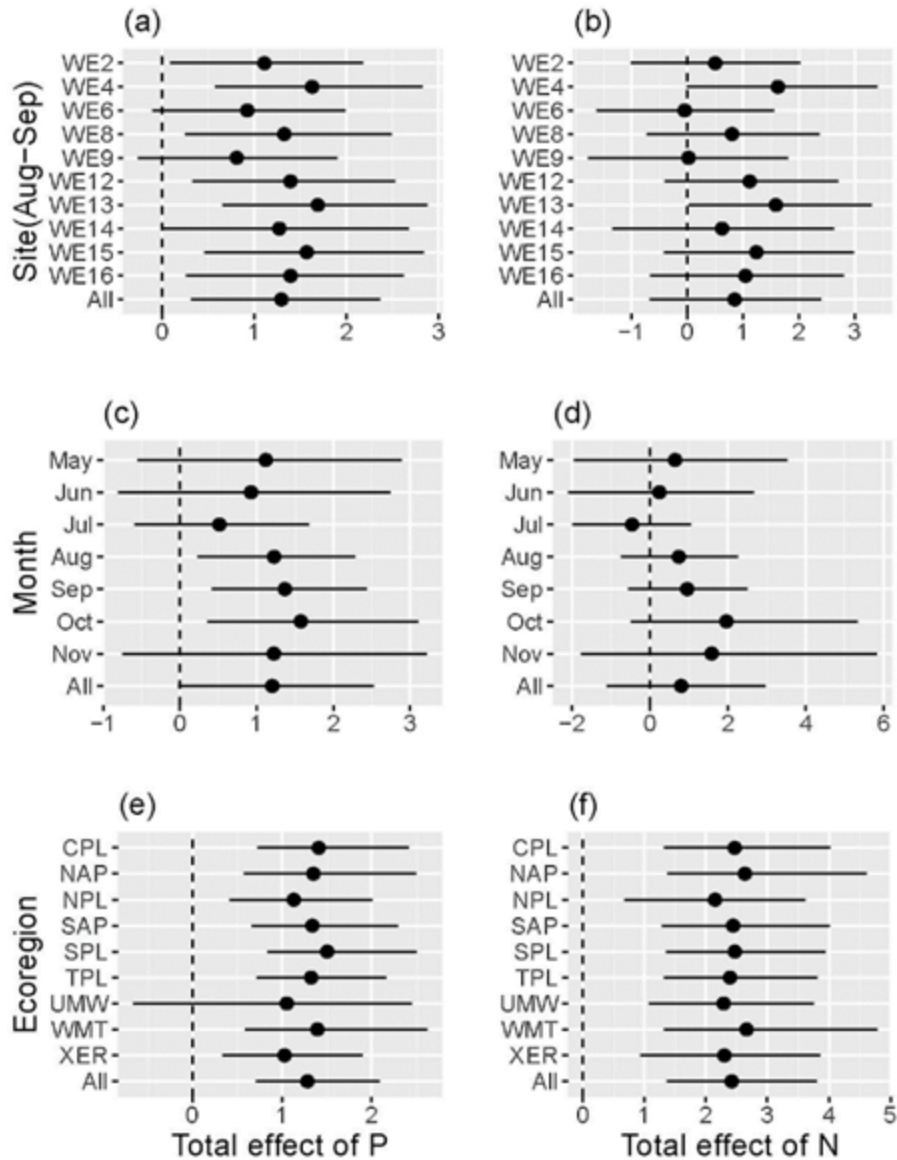
Figure 6. Forest plot for total effect of P and N on microcystin 1.6 µg/l threshold. a) Forest plot for total effect of P in WLE by stations in August and September; b) Forest plot for total effect of N in WLE by stations in August and September; c) Forest plot for total effect of P in WLE by months; d) Forest plot for total effect of N in WLE by months; e) Forest plot for total effect of P in NLA by ecoregions; f) Forest plot for total effect of N in NLA by ecoregions. R^2 for microcystin models were: NLA 1.6 = 0.54, and WLE 1.6 = 0.46.

Comparing N and P Dependence in WLE and NLA

Our comparisons between WLE and across-lake inferences show different coefficient values for both phosphorus and nitrogen in all models, though the magnitude of these differences varied by response variable and at different grouping levels. WLE had stronger effects from phosphorus but weaker effects from nitrogen in all models. These differences may be attributed in part to

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data collection and characteristics. While data were collected weekly or biweekly for WLE, water bodies in the NLA were sampled only once or twice between May and October. The time-series aspect of WLE data raises the possibility that nutrient-phytoplankton relationships vary throughout the bloom season in the lake. This is supported by the strong seasonal dependence we observed in the WLE dataset. However, for the NLA, the inferences are based on samples irrespective of the time they were collected. It is likely that the findings from the NLA would show similar seasonal dependence and that including repeated measurements in different seasons could potentially provide a different overall assessment of the roles of N and P in those lakes (see below). Additionally, our calculated total nitrogen effect in WLE does not include dissolved organic nitrogen, which may be important for *Microcystis* (Newell et al., 2019). We expect that this could amplify the impact of N, particularly in August-October when inorganic N is low, and the dependence on N is strongest.

Moreover, these differences may also be explained by the Ecological Fallacy phenomenon, which questions the legitimacy of generalizing regional coefficients (e.g., across-lake inferences by ecoregions) to the inference of local (lake-specific) relationships (Genser et al., 2015; Maas-Hebner et al., 2015). Aggregating data to a regional level may minimize or obscure the influence of data variability resulting in either over- or underestimation of coefficients (Liang et al., 2020). Although we used a Bayesian hierarchical approach to our regression models to represent variability, we did not allow the slope of independent variables to vary between individual water bodies in the NLA dataset, and this dataset does not describe seasonal variation. If the influence of local, lake-specific factors is greater than ecoregional patterns in HAB drivers—as shown in previous studies (Wagner et al., 2021; Read et al., 2015)—not allowing slopes to vary from lake to lake could be a reason for the discrepancy.

In this study, we assumed that the relationships between chlorophyll-a, cyanobacteria biomass, microcystin concentration, and the abiotic factors influencing them could be analyzed as bivariate correlations. However, this model assumption does not fully reflect the complex biotic processes underlying the interactions between abiotic factors and HABs within and across lakes. Numerous studies have shown that abiotic factors, such as temperature, pH, conductivity, and turbulence, can also influence the growth and toxin production by cyanobacteria, including *Microcystis* (Davis et al., 2009; Chaffin et al., 2018; Liu et al., 2019; Griffith and Gobler, 2020). Moreover, the introduction of invasive dreissenid mussel species contributes to shifts in phytoplankton community structure and often favors toxic cyanobacterial strains due to increased water clarity, nutrient ratio alterations, and selective trophic interactions (Idrisi et al., 2001; Idrisi et al., 2001; Fishman et al. 2010; De Stasio et al., 2014; Vanderploeg et al.,2001,2009). Our study focused mainly on the effects of nitrogen and phosphorus. Though we accounted for the independent effects of other abiotic factors, there are many other forces influencing HAB size and toxicity at different spatial scales—climate change, invasive species, and nutrients, micronutrient availability, and even tectonics to name a few (Hallegraeff, 1993; Anderson, 2009; Chimera et al., 2010; Wagner et al., 2021). However, despite the uncertainty

about the roles of these other drivers, understanding the nature and magnitude of the relationships between abiotic factors and HABs can help inform decision-makers on how to manage freshwater bodies.

Management implications

Extensive research has established the relationship between high concentrations of phosphorus and HAB occurrence (Schindler et al., 2016; Fastner et al., 2016). In phosphorus-limited environments, reducing available phosphorus can help mitigate algae growth (Lin et al., 2016). However, there is also evidence that in some locations regulating total phosphorus inputs has not been enough (Havens and Frazer, 2015; Xu et al., 2010; Paerl et al., 2004; Paerl, 2009). Despite the decrease in total phosphorus loads in the WLE basin in the last few decades, the amount of soluble reactive phosphorus—more readily available for phytoplankton uptake—has increased as a result of agricultural conservation practices (Baker et al., 2014; Jarvie et al., 2017). Studies have also shown that nitrogen could play a secondary role in HABs, contributing to the prevalence of more toxic species (Jankowiac et al., 2019; Wagner et al., 2021).

Although our study supports the argument that P is still the primary driver of HABs in WLE (Obenour et al., 2014), the great variability between stations and months suggests that there may not be a single relationship characterizing phosphorus effects on HABs. The strength and direction of these relationships fall within a spectrum dependent on the ecosystem's characteristics and its responses to seasonality. In our analysis of WLE data, we found higher coefficients of phosphorus during late summer months and stations further away from the Maumee River, similarly to what was previously described in Rowland et al. (2019). The effect of nitrogen varied greatly within the lake and was higher during August and September in stations 4 and 15; this is consistent with the idea that nitrogen might become the limiting or co-limiting nutrient in certain sites for specific seasons (Chaffin et al., 2013). These findings suggest that controlling P inputs should remain a priority, as stipulated in the GLWQA (GLWQA Nutrients Annex Subcommittee, 2015). However, decreasing available nitrogen later in the season may offer additional benefits in terms of toxin concentration or growth of cyanobacteria.

References
Anderson, D.M., 2009. Approaches to monitoring, control and management of harmful algal blooms (HABs). Ocean & Coastal Management 52, 342-347.
Baker, D., Confesor, R., Ewing, D., Johnson, L., Kramer, J., Merryfield, B., 2014. Phosphorus loading to Lake Erie from the Maumee, Sandusky and Cuyahoga rivers: The importance of bioavailability. Journal of Great Lakes Research 40, 502-517.

Barnard, M.A., Chaffin, J.D., Plaas, H.E., Boyer, G.L., Wei, B., Wilhelm, S.W., Rossignol, K.L., Braddy, J.S., Bullerjahn, G.S., Bridgeman, T.B., 2021. Roles of Nutrient Limitation on Western Lake Erie CyanoHAB Toxin Production. Toxins 13, 47.

Bürkner, P.-C., 2017. Advanced Bayesian multilevel modeling with the R package brms. arXiv preprint arXiv:1705.11123.

Bürkner, P.-C., 2017. brms: An R package for Bayesian multilevel models using Stan. Journal of Statistical Software 80, 1-28.

Burtner, A., Kitchens, C., Fyffe, D., Godwin, C., Johengen, T., Stuart, D., Errera, R., Palladino, D., Fanslow, D., Gossiaux, D., 2020. Physical, chemical, and biological water quality data collected from a small boat in western Lake Erie, Great Lakes from 2019-04-30 to 2019-10-07 (NCEI Accession 0209116). NOAA National Centers for Environmental Information.

Burtner, A., Palladino, D., Kitchens, C., Fyffe, D., Johengen, T., Stuart, D., Fanslow, D., Gossiaux, D., 2019. Physical, chemical, and biological water quality data collected from a small boat in western Lake Erie, Great Lakes from 2012-05-15 to 2018-10-09 (NCEI Accession 0187718). NOAA National Centers for Environmental Information, Lake Erie.

Cha, Y., Stow, C.A., 2014. A Bayesian network incorporating observation error to predict phosphorus and chlorophyll a in Saginaw Bay. Environmental Modelling & Software 57, 90-100.

Chaffin, J.D., Bridgeman, T.B., Bade, D.L., Mobilian, C.N., 2014. Summer phytoplankton nutrient limitation in Maumee Bay of Lake Erie during high-flow and low-flow years. Journal of Great Lakes Research 40, 524-531.

Chaffin, J.D., Davis, T.W., Smith, D.J., Baer, M.M., Dick, G.J., 2018. Interactions between nitrogen form, loading rate, and light intensity on Microcystis and Planktothrix growth and microcystin production. Harmful Algae 73, 84-97.

Chimera, C.G., Buddenhagen, C.E., Clifford, P.M., 2010. Biofuels: the risks and dangers of introducing invasive species. Biofuels 1, 785-796.

Chitikela, S.R., Ritter, W.F., 2017. The Total Phosphorus with Point and Non-Point Inflows to Great Lakes—A Critical Review and GLWQA Targets, World Environmental and Water Resources Congress 2017, pp. 453-467.

Davis, T.W., Berry, D.L., Boyer, G.L., Gobler, C.J., 2009. The effects of temperature and nutrients on the growth and dynamics of toxic and non-toxic strains of Microcystis during cyanobacteria blooms. Harmful Algae 8, 715-725.

De Stasio, B.T., Schrimpf, M.B., Cornwell, B.H., 2014. Phytoplankton communities in Green Bay, Lake Michigan after invasion by dreissenid mussels: increased dominance by cyanobacteria. Diversity 6, 681-704.

Fastner, J., Abella, S., Litt, A., Morabito, G., Vörös, L., Pálffy, K., Straile, D., Kümmerlin, R., Matthews, D., Phillips, M.G., 2016. Combating cyanobacterial proliferation by avoiding or treating inflows with high P load—experiences from eight case studies. Aquatic Ecology 50, 367-383.

Fishman, D.B., Adlerstein, S.A., Vanderploeg, H.A., Fahnenstiel, G.L., Scavia, D., 2010. Phytoplankton community composition of Saginaw Bay, Lake Huron, during the zebra mussel (Dreissena polymorpha) invasion: a multivariate analysis. Journal of Great Lakes Research 36, 9-19.

Flynn, K.J., McGillicuddy, D.J., 2018. Modeling marine harmful algal blooms: Current status and future prospects. Harmful Algal Blooms: A Compendium Desk Reference, 115-134.

Gobler, C.J., Burkholder, J.M., Davis, T.W., Harke, M.J., Johengen, T., Stow, C.A., Van de Waal, D.B., 2016. The dual role of nitrogen supply in controlling the growth and toxicity of cyanobacterial blooms. Harmful Algae 54, 87-97.

GLWQA Nutrients Annex Subcommittee. (2015). Recommended Binational Phosphorus Targets to Combat Lake Erie Algal Blooms

Griffith, A.W., Gobler, C.J., 2020. Harmful algal blooms: a climate change co-stressor in marine and freshwater ecosystems. Harmful Algae 91, 101590.

Gronewold, A.D., Borsuk, M.E., 2010. Improving water quality assessments through a hierarchical Bayesian analysis of variability. Environmental Science & Technology 44, 7858-7864.

Hallegraeff, G.M., 1993. A review of harmful algal blooms and their apparent global increase. Phycologia 32, 79-99.

Harke, M.J., Steffen, M.M., Gobler, C.J., Otten, T.G., Wilhelm, S.W., Wood, S.A., Paerl, H.W., 2016. A review of the global ecology, genomics, and biogeography of the toxic cyanobacterium, *Microcystis* spp. Harmful Algae 54, 4-20.

Harrison, P.J., Piontkovski, S., Al-Hashmi, K., 2017. Understanding how physical-biological coupling influences harmful algal blooms, low oxygen and fish kills in the Sea of Oman and the Western Arabian Sea. Marine Pollution Bulletin 114, 25-34.

Havens, K., Frazer, T., 2012. Rethinking the Role of Nitrogen and Phosphorus in the Eutrophication of Aquatic Ecosystems1. Institute of Food and Agricultural Sciences, University of Florida.

Heisler, J., Glibert, P.M., Burkholder, J.M., Anderson, D.M., Cochlan, W., Dennison, W.C., Dortch, Q., Gobler, C.J., Heil, C.A., Humphries, E., 2008. Eutrophication and harmful algal blooms: a scientific consensus. Harmful Algae 8, 3-13.

Herlihy, A.T., Paulsen, S.G., Sickle, J.V., Stoddard, J.L., Hawkins, C.P., Yuan, L.L., 2008. Striving for consistency in a national assessment: the challenges of applying a reference-condition approach at a continental scale. Journal of the North American Benthological Society 27, 860-877.

Ho, J.C., Michalak, A.M., 2020. Exploring temperature and precipitation impacts on harmful algal blooms across continental US lakes. Limnology and Oceanography 65, 992-1009.

Huo, S., Ma, C., Xi, B., Gao, R., Deng, X., Jiang, T., He, Z., Su, J., Wu, F., Liu, H., 2014. Lake ecoregions and nutrient criteria development in China. Ecological Indicators 46, 1-10.

Idrisi, N., Mills, E.L., Rudstam, L.G., Stewart, D.J., 2001. Impact of zebra mussels (Dreissena polymorpha) on the pelagic lower trophic levels of Oneida Lake, New York. Canadian Journal of Fisheries and Aquatic Sciences 58, 1430-1441.

Jankowiak, J., Hattenrath‑Lehmann, T., Kramer, B.J., Ladds, M., Gobler, C.J., 2019. Deciphering the effects of nitrogen, phosphorus, and temperature on cyanobacterial bloom intensification, diversity, and toxicity in western Lake Erie. Limnology and Oceanography 64, 1347-1370.

Jarvie, H.P., Johnson, L.T., Sharpley, A.N., Smith, D.R., Baker, D.B., Bruulsema, T.W., Confesor, R., 2017. Increased soluble phosphorus loads to Lake Erie: Unintended consequences of conservation practices? Journal of Environmental Quality 46, 123-132.

Jeppesen, E., Søndergaard, M., Jensen, J.P., Havens, K.E., Anneville, O., Carvalho, L., Coveney, M.F., Deneke, R., Dokulil, M.T., Foy, B., 2005. Lake responses to reduced nutrient loading–an analysis of contemporary long‑term data from 35 case studies. Freshwater Biology 50, 1747-1771.

Jetoo, S., Grover, V.I., Krantzberg, G., 2015. The Toledo drinking water advisory: suggested application of the water safety planning approach. Sustainability 7, 9787-9808.

Kim, K., Mun, H., Shin, H., Park, S., Yu, C., Lee, J., Yoon, Y., Chung, H., Yun, H., Lee, K., 2020. Nitrogen stimulates Microcystis-dominated blooms more than phosphorus in river conditions that favor non-nitrogen-fixing genera. Environmental Science & Technology 54, 7185-7193.

Levy, S., 2017. Microcystis rising: why phosphorus reduction isn't enough to stop cyanoHABs. National Institute of Environmental Health Sciences.

Liang, Z., Dong, F., Qian, S.S., Liu, Y., Chen, H., Lu, W., 2020. Ecoregional or site-specific lake nutrient criteria? Evidence from ecological fallacy. Ecological Indicators 111, 105989.

Lin, S., Litaker, R.W., Sunda, W.G., 2016. Phosphorus physiological ecology and molecular mechanisms in marine phytoplankton. Journal of Phycology 52, 10-36.

Liu, M., Ma, J., Kang, L., Wei, Y., He, Q., Hu, X., Li, H., 2019. Strong turbulence benefits toxic and colonial cyanobacteria in water: A potential way of climate change impact on the expansion of Harmful Algal Blooms. Science of the Total Environment 670, 613-622.

Malve, O., Qian, S.S., 2006. Estimating nutrients and chlorophyll a relationships in Finnish lakes. Environmental Science & Technology 40, 7848-7853.

Newell, S.E., Davis, T.W., Johengen, T.H., Gossiaux, D., Burtner, A., Palladino, D., McCarthy, M.J., 2019. Reduced forms of nitrogen are a driver of non-nitrogen-fixing harmful cyanobacterial blooms and toxicity in Lake Erie. Harmful Algae 81, 86-93.

Obenour, D.R., Gronewold, A.D., Stow, C.A., Scavia, D., 2014. Using a Bayesian hierarchical model to improve Lake Erie cyanobacteria bloom forecasts. Water Resources Research 50, 7847-7860.

Paerl, H.W., 2009. Controlling eutrophication along the freshwater–marine continuum: dual nutrient (N and P) reductions are essential. Estuaries and Coasts 32, 593-601.

Paerl, H.W., Scott, J.T., McCarthy, M.J., Newell, S.E., Gardner, W.S., Havens, K.E., Hoffman, D.K., Wilhelm, S.W., Wurtsbaugh, W.A., 2016. It takes two to tango: When and where dual nutrient (N & P) reductions are needed to protect lakes and downstream ecosystems. Environmental Science & Technology 50, 10805-10813.

Paerl, H.W., Valdes, L.M., Joyner, A.R., Piehler, M.F., Lebo, M.E., 2004. Solving problems resulting from solutions: evolution of a dual nutrient management strategy for the eutrophying Neuse River Estuary, North Carolina. Environmental Science & Technology 38, 3068-3073.

Paerl, H.W., Xu, H., Hall, N.S., Zhu, G., Qin, B., Wu, Y., Rossignol, K.L., Dong, L., McCarthy, M.J., Joyner, A.R., 2014. Controlling cyanobacterial blooms in hypertrophic Lake Taihu, China: will nitrogen reductions cause replacement of non-N_2 fixing by N_2 fixing taxa? PloS one 9, e113123.

Qian, S.S., Stow, C.A., Borsuk, M.E., 2003. On monte carlo methods for Bayesian inference. Ecological Modelling 159, 269-277.

Qian, S.S., Stow, C.A., Nojavan, F., Stachelek, J., Cha, Y., Alameddine, I., Soranno, P., 2019. The implications of Simpson's paradox for cross-scale inference among lakes. Water Research 163, 114855.

R Core Team, 2020. R: A language and environment for statistical computing. R Foundation for Statistical Computing.

Read, E.K., Patil, V.P., Oliver, S.K., Hetherington, A.L., Brentrup, J.A., Zwart, J.A., Winters, K.M., Corman, J.R., Nodine, E.R., Woolway, R.I., 2015. The importance of lake‑specific characteristics for water quality across the continental United States. Ecological Applications 25, 943-955.

Richards, R.P., ker, D.B., Crumrine, J.P., 2009. Improved water quality in Ohio tributaries to Lake Erie: A consequence of conservation practices. Journal of Soil & Water Conservation 64, 200-211.

Rowland, F.E., Stow, C.A., Johengen, T.H., Burtner, A.M., Palladino, D., Gossiaux, D.C., Davis, T.W., Johnson, L.T., Ruberg, S., 2019. Recent patterns in Lake Erie phosphorus and chlorophyll a concentrations in response to changing loads. Environmental Science & Technology 54, 835-841.

Sanseverino, I., Conduto, D., Pozzoli, L., Dobricic, S., Lettieri, T., 2016. Algal bloom and its economic impact. European Commission, Joint Research Centre Institute for Environment and Sustainability.

Schindler, D.W., Carpenter, S.R., Chapra, S.C., Hecky, R.E., Orihel, D.M., 2016. Reducing phosphorus to curb lake eutrophication is a success. Environmental Science & Technology 50, 8923-8929.

Schmale III, D.G., Ault, A.P., Saad, W., Scott, D.T., Westrick, J.A., 2019. Perspectives on harmful algal blooms (HABs) and the cyber biosecurity of freshwater systems. Frontiers in Bioengineering and Biotechnology 7, 128.

Stan Development Team, 2020. RStan: the R interface to Stan. R package version 2.21.2. http://mc-stan.org/.

Stumpf, R.P., Wynne, T.T., Baker, D.B., Fahnenstiel, G.L., 2012. Interannual variability of cyanobacterial blooms in Lake Erie. PloS one 7, e42444.

U.S. EPA. 1972. Clean Water Act. 33 U.S.C §§ 1251 et seq

U.S. EPA. 1998. National Strategy for the Development of Regional Nutrient Criteria.

U.S. EPA. 2010. National Aquatic Resource Surveys. National Lakes Assessment 2007. Available from U.S. EPA web page: https://www.epa.gov/national-aquatic-resource-surveys/data-national-aquatic-resource-surveys. Date accessed: 2020-05-28.

U.S. EPA. 2015 Drinking Water Health Advisories for Two Cyanobacterial Toxins.

U.S. EPA. 2016-a. National Aquatic Resource Surveys. National Lakes Assessment 2012. Available from U.S. EPA web page: https://www.epa.gov/national-aquatic-resource-surveys/data-national-aquatic-resource-surveys. Date accessed: 2020-05-28.

U.S. EPA. 2016-b. National Aquatic Resource Surveys. National Lakes Assessment 2012. Available from U.S. EPA web page: https://www.epa.gov/national-aquatic-resource-surveys/upper-midwest-ecoregion-national-lakes-assessment-2012-results

U.S. EPA, 2018. U.S. Action Plan for Lake Erie.

Vanderploeg, H.A., Liebig, J.R., Carmichael, W.W., Agy, M.A., Johengen, T.H., Fahnenstiel, G.L., Nalepa, T.F., 2001. Zebra mussel (*Dreissena polymorpha*) selective filtration promoted toxic Microcystis blooms in Saginaw Bay (Lake Huron) and Lake Erie. Canadian Journal of Fisheries and Aquatic Sciences 58, 1208-1221.

Vanderploeg, H.A., Johengen, T.H., Liebig, J.R., 2009. Feedback between zebra mussel selective feeding and algal composition affects mussel condition: did the regime changer pay a price for its success? Freshwater Biology 54, 47-63.

Vehtari, A., Gabry, J., Magnusson, M., Yao, Y., Bürkner, P., Paananen, T., Gelman, A., 2020. loo: Efficient leave-one-out cross-validation and WAIC for Bayesian models. R package version 2.4.1.

Wagner, N.D., Quach, E., Buscho, S., Ricciardelli, A., Kannan, A., Naung, S.W., Phillip, G., Sheppard, B., Ferguson, L., Allen, A., 2021. Nitrogen form, concentration, and micronutrient availability affect microcystin production in cyanobacterial blooms. Harmful Algae 103, 102002.

Wilhelm, S.W., Bullerjahn, G.S., McKay, R.M.L., 2020. The complicated and confusing ecology of Microcystis blooms. Mbio 11.

Withers, P.J., Neal, C., Jarvie, H.P., Doody, D.G., 2014. Agriculture and eutrophication: where do we go from here? Sustainability 6, 5853-5875.

Xu, H., Paerl, H.W., Qin, B., Zhu, G., Gaoa, G., 2010. Nitrogen and phosphorus inputs control phytoplankton growth in eutrophic Lake Taihu, China. Limnology and Oceanography 55, 420-432.

Yuan, L.L., Pollard, A.I., 2017. Using national-scale data to develop nutrient–microcystin relationships that guide management decisions. Environmental Science & Technology 51, 6972-6980.

Harmful Algal Blooms in Lake Erie: A Case Study on Values, Attitudes, and Policy Preferences on Nutrient Management

1 Introduction

Maintaining the ecosystem services of the Great Lakes requires cooperation among many stakeholders with different interests. Optimizing management and policy-making requires a clear understanding of stakeholder beliefs and community structure. One recent issue is the impacts and management of harmful algal blooms (HABs). Despite Lake Erie's socio-economic importance, it has been affected by HABs since the 1950s (Allinger et al., 2013). The effect HABs have on Lake Erie is partly the result of the wide-ranging impacts and the challenge of bringing together various stakeholder types to address the problem.

1.1 Harmful Algal Blooms in Lake Erie

Water quality issues caused by HABs affect the natural environment and recreation, household use, and fisheries (Dai et al., 2012; Kim et al., 2020). Lake Erie provides drinking water to over 11 million people and $7 billion in associated annual revenue (US Environmental Protection Agency, 2004). Algal toxins, such as microcystin, can cause liver and kidney damage if accumulated in the human body (Harke et al., 2016) and can make water unsuitable for drinking and swimming as a result. In response to elevated microcystin concentrations in drinking water in 2014, Toledo declared a state of emergency and issued a "do not drink" water quality advisory (Jetoo et al., 2015). Furthermore, there is an estimated annual loss of $305 million in tourist revenue in Ohio and an estimated $25 million in Michigan's Monroe county (Bingham & Kinnel, 2020) due to HABs. Between 2011 and 2014, the Lake Erie fishing industry lost $5.58 million (Wolf et al., 2017). The impact of HABs, driven by runoff, remains a concern to this day.

HABs are primarily the result of excess nutrient inputs from anthropogenic activity such as agricultural fertilizer use, urban development, and fossil fuels (Robertson et al., 2011). Although phosphorus (P) from fertilizer is known to be a primary driver of HABs and has received the most attention from regulators, recent work has shown that nitrogen (N) could also play a role in growth and toxicity (Newell et al., 2019; Chaffin et al., 2018). In response to the growing threat of HABs in Lake Erie during the mid-20th century, the United States Congress expanded the Clean Water Act (CWA) and signed the Great Lakes Water Quality Agreement (GLWQA) with Canada in 1972 (IJC, 1972). Following these changes, upgrading and expanding sewage treatment plants and regulating P in household detergents led to dramatic decreases in P

loading and algal production in Lake Erie (De Pinto et al., 1986). By the mid-1980s, total P loading had decreased by 50% (Allinger et al., 2013). However, since the early 2000s, HABs have returned and often affect the water quality in Lake Erie's western basin (Sayers et al., 2019; Watson et al., 2016).

The GLWQA set a precedent between the United States and Canada to reach annual nutrient loading targets (International Joint Commission, 1987). In response to the return of HABs in the 2000s, the GLWQA was amended to include a goal to reduce phosphorus loading in Lake Erie by 40% and implementation of adaptive management (IJC, 2012; Stow et al., 2020). Although phosphorus regulations since the 1970s have been partially successful in reducing total P loads, the current target of a 40% reduction in phosphorus loading will take time to achieve (Wilson et al., 2019). U.S. implementation of nutrient management for Lake Erie rests in the state governments' hands (Berardo et al., 2019). In both Michigan and Ohio, there is a heavy legislative emphasis on agricultural fertilizer use, including the "4R" approach, which stands for "right source, right rate, right time, and right place"(IJC, 2014; Bruulsema et al., 2009). Changes in agricultural practices could be achieved through restrictions and fines or voluntary programs involving farmers' engagement (IJC, 2014; Ohio EPA, 2013). Approaches to managing HABs in Lake Erie have mainly been through voluntary programs; however, this has not led to nutrient reduction levels necessary to successfully manage Lake Erie HABs (Wilson et al., 2019). The lack of nutrient reduction suggests that the current policy is suboptimally aligned with stakeholder needs and beliefs. A better understanding of those stakeholders may enable developing policies that produce higher collaboration and stakeholder buy-in rates.

1.2 Stakeholders' Values, Attitudes, and Beliefs in Decision Making

Stakeholders can play a critical role in decision-making processes. Their engagement can provide details, inputs, risk assessments, and information to widen the understanding and scope of various issues (Vilet et al., 2020), which can be used in targeted ways to develop information products and forecasts (Gill et al., 2018). These issues can include economic risks, water use, environmental impacts, public health impacts, and perceptions. Input is also critical for understanding the feasibility and effectiveness of communication and proposed changes. Stakeholder input, cooperation, and commitment are important aspects of decision-making.

Participants' values and what an individual believes to be right or wrong often shape decision-making processes (Ravlin & Meglino, 1987; Fritzsche & Oz, 2007; Schwartz, 2012, Pitas et al., 2019). According to the Values-Attitudes-Beliefs framework, a person's values directly influence their attitudes, influencing their beliefs (Homer & Kahle 1988, Vaske & Donnelly, 1999). When these values differ among individuals or groups, there tends to be a more difficult time compromising high-impact decisions, resulting in a lack of collaborative management (Henry et al., 2010). Although collaboration between a diverse group of stakeholders often seems unlikely, there are many examples of productive collaborations among stakeholders. Examples of successful collaborations include HABs management in Asia and macrophyte Sargassum and ciguatera fish poisoning in the US Caribbean Islands (Anderson et al., 2019). However, various views on the best way to manage phosphorus loading result in many

strategies being attempted simultaneously. Each of these strategies may not be the best strategy for all stakeholders. Nonetheless, stakeholder collaborations are essential for establishing the best outcome.

1.3 Collaboration in the Lake Erie Watershed

The western Lake Erie watershed, and therefore its local stakeholders, includes Ohio, Michigan, Indiana, and Ontario. In the Lake Erie basin, government, non-government agencies (NGO), and private stakeholders play an essential role in nutrient management. Government stakeholders include local and federal government agencies that often invest in projects to mitigate the effects of HABs in Lake Erie. The NGO stakeholder type includes research institutions and advocacy groups that connect and communicate with landowners and farmers to understand and advance nutrient management strategies. NGOs also engage with other stakeholders and the general public to better educate them about the Lake Erie HABs issue. Private stakeholders include individuals and privately owned businesses that can often be affected by the targets/regulations. There can be more effective decision-making on the Lake Erie HABs issue with all three stakeholder types collaborating.

Although there are many management plans, programs, and laws tackling the Lake Erie HABs issue, there remains potential for disconnect between different stakeholders and management goals (Kalcic et al., 2016). For example, a study on the support for water quality regulations in the Ohio region of the Lake Erie watershed showed that people who worked in agriculture are less supportive of fines to regulate agricultural runoff (Guo et al., 2019). It is crucial to understand how various stakeholders have been affected by existing measures and perceive potential changes to implement efficient measures to control HABs(Gill et al., 2018).

A collaborative effort between all stakeholders is necessary to effectively and efficiently manage HABs in Lake Erie. This effort must navigate the variety of views and values the stakeholders possess and emphasize commitment and compromise from all stakeholders (Rissman and Carpenter, 2015). Locally, the GLWQA is an example of a productive collaboration as goals have been set to reduce the phosphorus loading into Lake Erie, and progress has been made toward meeting those goals (GLWQA Lake Objective; Scavia 2016). Although there are many instances of successful collaboration between stakeholders, differences in values, attitudes, and policy preferences can inhibit collaboration, resulting in barriers to implementing and adopting new policies (Henry et al., 2010).

Another method of understanding stakeholder collaboration is to understand the social network of Lake Erie HABs management. Networks characterize the relationships that individuals or entities have with each other and have several applications in understanding water resources management. Recognizing how Lake Erie stakeholders collaborate provides another aspect of understanding potential barriers and opportunities to successful HABs management.

In this study, we seek to gain insight into the values, attitudes, and beliefs of different groups of Lake Erie stakeholders. We also seek to gain insight into the potential barriers and opportunities to HAB management.

1.4 Study Aims

This study aims to understand the similarities and differences in Lake Erie stakeholders' values, attitudes, and perceptions. The specific research questions we addressed are:

- RQ1: Do different Lake Erie stakeholder types hold different environmental values?
- RQ2: Do stakeholders have shared policy attitudes?
- RQ3: Do stakeholders have shared policy preferences?
- RQ4: How much are stakeholders already working together?

2 Methods

2.1 General study design

We conducted a total of twenty-nine interviews of stakeholders spread across the government, NGO, and private stakeholder types; each is associated with the Lake Erie watershed decision-making process. All research questions were given a specific section in the interview guide (Appendix B1). The interviews were semi-structured and were coded to capture key themes and research questions. Some of these themes are how these groups differ in their values, attitudes, and perceptions; where they get their information on Lake Erie HABs; what management approaches they support. We also used the interview responses to characterize the relationships among those stakeholders using social network analysis.

2.2 Identifying stakeholders

We created the list of stakeholders in the Lake Erie watershed through searches in previous publications, regional meetings, and websites for the organizations. We also used a snowball sampling method to augment the list identified in our initial search during the interview's closing remarks. The snowball sampling method consisted of the interviewer asking the interviewee if they had any suggested contacts for this research. This sampling method resulted in 17% of the people who were interviewed.

After a list of 102 potential stakeholders was established, each stakeholder was categorized into their respective stakeholder types based on the organization they represent. These stakeholder types were the government, private, and NGO stakeholder types. The stakeholders were then contacted to schedule an interview. Of the 102 stakeholders we contacted by email, 29 agreed to participate in the study. Once the interview times and dates were set, the official consent form and the interview questions were sent to the interviewees.

2.3 Interview Questions

We developed a semi-structured interview guide with a combination of both Likert scale ranking and open-ended questions. This interview style allows interviewers to ask additional questions if an interesting or new line of information develops in the interview. There were five sections in the interview guide–four were based on the research questions, and a fifth section to characterize the interviewee's demographics. The demographics section told us that 69% of the interviewees were male, the average age was fifty-one, and 90% identified as caucasian.

The first section contained ten questions used to gauge stakeholders' values. All ten questions had a Likert scale format where the interviewee was asked to answer on a scale of 1-5, with 1 being strongly disagree and 5 strongly agree. These questions were phrased to allow interviewees to strongly agree with the statement if they believe the environment has intrinsic

value and should be managed to enable public use without degradation. The second section was based on identifying stakeholder attitudes towards Lake Erie and HABs management. This section contained thirteen questions that were a combination of Likert scale ranking and open-ended questions; eight were specific to HABs. The third section focused on the stakeholders' policy preferences and consisted of six questions that were a mix of the two question types. The fourth section incorporated a network analysis by providing a list of the 102 stakeholders.

The interviews were conducted virtually on Google Meet, which allowed the Google extension Tactiq to create a transcript of the interview. Tactiq was only used if the interviewee consented to be recorded for transcription purposes. Twenty-eight out of twenty-nine interviewees agreed to be recorded and have complete transcripts. The transcripts were then quality checked and edited for accuracy.

2.4 Quantitative Data Analysis

We performed a Kruskal-Wallis test to assess how value scores differed among stakeholder types (R-core). This non-parametric approach was chosen due to the small size of our data (n=29). Value scores derived from questions Q1-Q10 were averaged to get a value score for each person. When the p-value was less than 0.05, we rejected the null hypothesis.

For every ranking question, we assigned the scores 1, 2, 3,..., (n-1), n to interviewees' highest to lowest options. If the interviewee ranked multiple options in the same order, we gave these options identical scores to ensure the total score of all options for one question is equal to $n*(1+n)/2$. Then we calculated the portions of each option in every stakeholder type/cluster as follows: $Portion = m \times n - \sum_{k=1}^{m} \alpha_k$. Where m is the number of individuals in each group/cluster, n is the number of options, α_k is the different score individuals got for the same option. We then used the chi-square test to ask whether the answers are distributed among stakeholder types.

2.5 Qualitative Data Analysis

We coded and analyzed qualitative data in NVivo (Release 1.0, QSR International, Doncaster, Australia). We created a codebook that was categorized around the interview questions (Appendix B3). Questions in the policy preferences category analyzed how interviewees viewed current policies and recommendations for future policies. Questions in the attitudes category analyzed how interviewees viewed Lake Erie, its environmental issues, and management strategies. The results from the codebook were summarized into percentages based on the interviewee responses. After the general summary was complete, the responses were split into values clusters and stakeholder types to determine if the attitudes and policy preferences were similar.

2.6 Cluster Creation

Since individuals' values tend to be correlated, and the collective set of values affects their decisions, we attempted to outline groups of individuals with similar values using ordination and clustering. We used stakeholder answers to questions 1-10 to divide them into

three 'values' clusters. We first reversed the scales to questions 2, 4, and 8 to make the directionality consistent with the rest of the questions. The missing values were assigned the averages of the same question answered by others. Then we performed a Principal Component Analysis, followed by a Cluster Analysis, using the function 'kmeans' in R and setting k=3. After generating the three value clusters, we performed a permutation test in R using the 'independence_test' function in the 'coin' package to check whether the three stakeholder types were randomly assorted to their cluster (Hothorn et al., 2006). We used the resulting value clusters to help analyze research questions 2 and 3.

2.7 Network Analysis

We used network analysis to describe the interactions and information exchange among our interviewees' organizations and the larger community around Lake Erie. Three organizations had two interviewees; therefore, we collapsed the interviewee's responses into one response, maintaining all stated connections. The collapsing of these responses resulted in twenty-four total organizations in the analysis. These connections were collected through two interview questions. The first question prompted the interviewee to recognize whether they have recently worked with any organizations on the provided list (Appendix B1). The second question asked if any other organizations the interviewee worked with were not on the provided list. We placed these connections into a binary matrix, where a stated connection received the value of 1 and no connection received 0. For organizations that had reported ties but were not interviewed, we assigned a stakeholder type utilizing the same methods we did when identifying stakeholders. We used the R package 'igraph' (Csardi and Nepusz 2006) to create a network map that displays two attributes associated with each stakeholder: whether they were interviewed and which stakeholder type they belonged to.

We analyzed the connection density of all organizations and the homophily of interviewed organizations. The connection density was explained by characterizing the total number of connections associated with each organization involved in the network. Homophily was calculated using the External-Internal, or EI Homophily Index (Lizardo 2021), calculated as follows: $EI = \frac{External - Internal}{External + Internal}$. This metric is defined by scoring how often a node interacts with others of a similar attribute, ranging from -1 to 1. In our study, a negative index means there are more ties to the same stakeholder type (homophilic). In contrast, a positive value means there are more ties to differing stakeholder types (heterophilic). All index values from organizations in a stakeholder type were then averaged together to give a stakeholder type homophily index. To account for the distribution of the stakeholder types in our network, we calculated the 'expected' homophily index values for each sector. This expected value is calculated using the previous formula under the assumption that a hypothetical individual in each stakeholder type collaborates with all other stakeholders in the network. The expected homophily value allows us to determine if stakeholder types are more or less homophilic, considering the network's pool of stakeholders. We then compared the measured Homophily Index values against the expected values to determine whether each stakeholder type had more internal versus external connections.

3 Results

3.1 Comparing stakeholder values (RQ1)

We expected to find that each of the stakeholder types would have different values when compared to the other stakeholder types. We found that only questions 4 and 10 were significantly different among the three different stakeholder types for the ten value questions. Both questions had p-values of 0.03 using the Kruskal-Wallis test. This result indicates that the three stakeholder types share similar values for most of the questions, which is not consistent with what we expected. However, there is reason to believe that scores for individual questions will show high within-group variability and that differences based on each value question may not adequately describe individuals (see section 6).

3.2.1 Stakeholder views of Lake Erie water quality

All interviewees agreed that Lake Erie is vital to the region, as expected since all interviewees work or live around the lake. Interviewees' perception of Lake Erie's water quality over the past ten years ranged from good to poor. However, 58% of interviewees perceived the water quality to be poor. Interviewees who stated they had a positive perception of Lake Erie's water quality compared the quality to previous years. "I would say that Lake Erie has made a tremendous comeback, but it is continuing to struggle to maintain a respectable level of water quality." Most interviewees believed that HAB management should be prioritized, with the average ranking being 4.6 on a scale from 1 to 5. This result is consistent with the interviewee's perceived importance of the lake to the region, with the average ranking being 4.8. Most stakeholders believed that Lake Erie's importance is tied to its economic and ecological values. Household use and 'other' were ranked first amongst stakeholders in the NGO and government stakeholder types. The options 'political' and 'recreation' were not ranked first in any stakeholder type. The alternative options posed as the 'other' option were spiritual, symbolic, and transportation (Figure 2a). The people who responded 'other' had some sort of work or personal tie to their ranking.

Though the different stakeholder types shared views on Lake Erie's importance and water quality, there were differences in what they focused on when they explained their rankings. The NGO stakeholder type had the most people with more negative views on the current state of Lake Erie "When it is not choked with cyanobacteria, it may appear ok, but in truth, it is quite sick." The private stakeholder type had the most positive views on lake Erie's current status, but only four people out of 29 answered positively. These four positive views typically had to do with the lake's usability in the summer of 2020. "Currently, as of July 2020, it is great for fishing, great for recreation. We have a minimal problem this year with an algal bloom". The government stakeholder type had the most neutral explanations to their rankings, generally describing the lake's function or explaining its good and bad aspects.

> "I would describe it as Lake Erie is part of the system of the five Great Lakes that are a huge source of freshwater for the region as well as being very important to our economic and human development of the area. Lake Erie, because it is the shallowest, the smallest,

the most biologically productive of those five Great Lakes, also has the highest human development in its watershed."

Overall, the main views of the interviewed stakeholders were that the water quality of Lake Erie is poor. Still, a good year can influence the current opinion on lake water quality.

3.2.2 Stakeholders' view of the role of nitrogen in HABs

When asked about what role nitrogen plays in influencing HABs, most interviewees from each stakeholder type stated that nitrogen has an effect. Of the NGO stakeholder type, 55% said that nitrogen generally affects HABs, while the other 45% said nitrogen affects the blooms' toxicity. In the private stakeholder type, 50% said nitrogen generally affects HABs, 25% said it affects the toxicity, and 25% said it affects bloom size. In the government stakeholder type, 37% said nitrogen generally affects HABs, 45% said it influences the toxicity, and 18% said it influences bloom size.

The role of nitrogen on HABs is being researched and debated by scientists; the stakeholders' views reflected this uncertainty. Two people said they did not feel they understood the science enough to answer the question, while others answered but prefaced that they are still reading articles about nitrogen's influence. With stakeholders having uncertainty in the effects of nitrogen, advocating for new policies regulating nitrogen might be challenging to find support for.

3.2.3 Stakeholders' policy attitudes

For each stakeholder type, a policy's effectiveness was ranked as the top consideration in accepting a policy, with 89% of all interviewees ranking it first, as the interviewees "would not accept a policy that they did not believe would work." Figure 2c shows that stakeholder acceptance was the top second choice with 54% of NGO, 50% of government, and 37% of private stakeholder types ranking it second. Among the barriers to HABs management, farmer engagement was the highest-ranked among the options given. More than 50% of the NGO and private stakeholder types interviewees ranked this option first. The options were more evenly ranked within the government stakeholder type, with the highest option (33%) being 'other,' representing weather, political will, and the economic status quo (Figure 2b).

3.3 Stakeholder policy preferences

Policy preferences were not significantly different between stakeholder types (Chi-Square test, p-value= 0.1362). However, the NGO stakeholder type preferred regulatory approaches more than the other two stakeholder types, with 81% of the NGO interviewees ranking regulatory approaches first, compared to the 50% and 57% of the interviewees from the government and private stakeholder types, respectively (Figure 2d).

Though people from the NGO stakeholder type said they would prefer regulatory approaches, many did not think it would be feasible. One NGO stakeholder type interviewee stated, "I think standards are important. Most farmers are trying to do the right thing, but farm operations vary widely…" when talking about why regulations may not be feasible. The private and government stakeholder types also preferred regulatory approaches but were split on what approach would be the most feasible. One private stakeholder type interviewee preferred

market-based approaches stating "any effective approach will be a long-term plan of market-based best practices in the ag community." Another private stakeholder type interviewee preferred stronger regulations stating, "We have gone from basically 2005 with completely voluntary efforts to try to stop the problem coming in from the land. It still has not worked fifteen years later. We need to get to the regulation portion and get something done". The variety of answers of what is most feasible from the private and government stakeholder types is likely due to the variety in their respective organizations' focus. In contrast, the NGO stakeholder type was primarily made up of interviewees who focused strongly on environmental protection with only a few farming/fishing-focused groups.

All stakeholder types believed that federal and state agencies should be in charge of HABs management. The private stakeholder type mentioned that stakeholders should be involved in the process, while the government stakeholder type also mentioned the word "collaboration" many times. One interviewee stated that "we really need all of these [organizations] together in a collaborative effort. There's no one person or agency that could do it alone". The NGO stakeholder type did not mention stakeholders' involvement or collaboration.

3.4 Creating clusters based on values (RQ1)

Since we did not find widespread or systematic differences among stakeholder types for each of the values, attitudes, and policy preferences questions, it is likely that the values and responses are better described collectively rather than individually. To understand whether participants' values influenced their attitudes and policy preferences, we grouped stakeholders into clusters based on the value questions in section one of the interview guide (Appendix B4). Figure 1 shows the grouping of the interviewees into values clusters. The first dimension (horizontal) represents the spectrum of environmental or economic priorities; this dimension explained 31.8% of the variation. Additionally, the second dimension (vertical) describes whether water should be managed for human benefit (top) or environmental benefit (bottom); this dimension explained 22.8% of the variation. Though there is a mixture of stakeholder types in each of the three values clusters, the stakeholder types were not evenly spread among the clusters. A permutation test showed that the clusters were significantly different from what would be expected from a random distribution of stakeholders (p-value=0.02). Cluster 1 did not have any interviewees from the government stakeholder type, while values Clusters 2 and 3 had all three stakeholder types represented.

Cluster 1 was centered around their stronger environmental values and belief that the environment should be managed primarily for human benefit. Cluster 2 was centered around their stronger economic values and belief that the environment should be managed primarily for human benefit. In contrast, Cluster 3 was centered on their stronger environmental values and their belief that the environment should not be managed primarily for human benefit. Many NGO stakeholder type stakeholders talked about how humans should not be considered separate from the environment when considering their answers to whether or not the environment should be managed primarily for human benefit. Although the values clusters reflect that the interviewees answered the values questions differently, it only explains approximately 50% of

the data. These value clusters have a wide range across the x-axis. Clusters 1 and 2 are close to overlapping near the center of the axis, which could be due to the shared interest most stakeholders have regarding Lake Erie water quality.
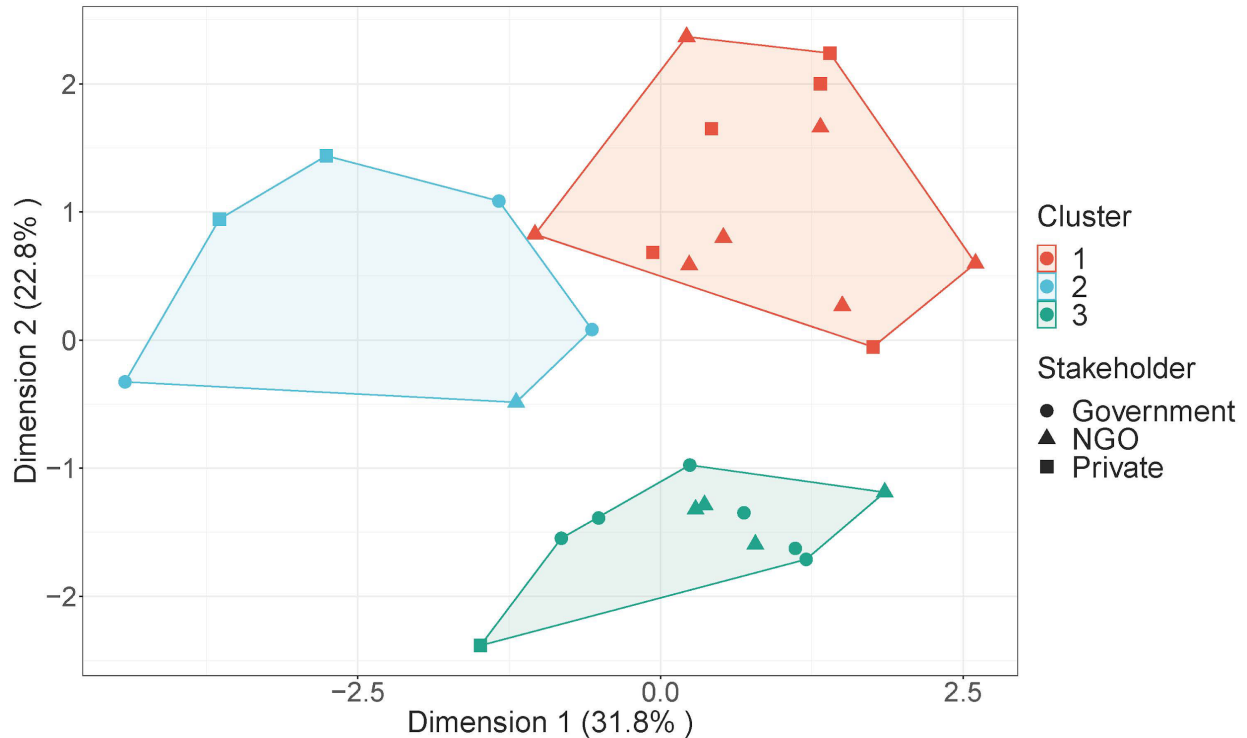

Figure 1. Principal component and cluster analysis of stakeholder responses. Each circle/triangle/square represents a single interviewee. In cluster 1 there are 12 interviewees (5 private, 7 NGO). In cluster 2 there are 6 interviewees (3 government, 1 private, 2 NGO). In cluster 3 there are 11 interviewees (1 private, 6 government, 4 NGO). The points on cluster 2 are all located around the edge of the cluster.

3.5 Attitudes towards Lake Erie management by cluster

We found slight differences in analyzing values clusters' answers regarding their policy attitudes. All value clusters generally ranked the ecologic and economic aspects of Lake Erie to be the most important; the other options were evenly prioritized between all value clusters (Figure 2a). In Cluster 1, many people had a more negative view of the current state of Lake Erie. They mentioned a lack of political will, capacity, and power as a challenge in agricultural runoff management. "I would say it is largely due to a lack of political will to put the necessary procedures in place". In Cluster 2, most people had neutral views on the current state of Lake Erie (4), while two people had negative views. Cluster 3 was less uniform in their answers about Lake Erie's current state when compared to the other values clusters, but they had the most people who gave a neutral response.

Figure 2c shows that stakeholder acceptance was the top second choice for value Clusters 1 and 2, with 64% and 50% of interviewees ranking it second, respectively. In value Cluster 2, public acceptance and their organizations' interest were tied for second at 33%. Across all of the

value clusters, the highest perceived barrier to HABs management was farmer engagement. However, in Cluster 2, scientific agreement was also perceived as a strong barrier as it was tied with farmer engagement at 33% (Figure 2b).

3.6 Comparing policy preferences by cluster(RQ3)

The three values clusters had significantly different preferences among regulatory, voluntary, and market-based approaches (Chi-Square, p-value= 0.0008). In Cluster 1, 81% of the interviewees ranked regulatory approaches first, and no one ranked voluntary approaches first (Figure 2d). Interviewees in this cluster often talked about how they think voluntary approaches are not beneficial.

> "My position would be to state that current voluntary policies are clearly failing. They're not effective at reducing the nutrient fluxes into the system because everyone expects no one to make an impact".

Cluster 2 preferred both market-based and regulatory approaches, with both ranking first by 40% of the interviewees in this value cluster. This cluster also believed that farmers should not be 'punished' more as they are already struggling. "To perform financially, we have to incentivize them in the positive, not be punitive in the negative.". Some interviewees suggested that there should be a way for farmers to pass the cost of implementing better practices through the supply chain. In Cluster 3, 60% of the interviewees ranked regulatory approaches first. When talking about what is feasible many people in this cluster believed that all aspects of the different policy approaches are needed to be effective. They also were more likely to talk about how political will might influence feasibility.

> "I think you are just going to have to incentivize the heck out of it. Either that or you are going to have to penalize people for damaging the environment, and we just haven't politically shown a backbone to do that as a nation."
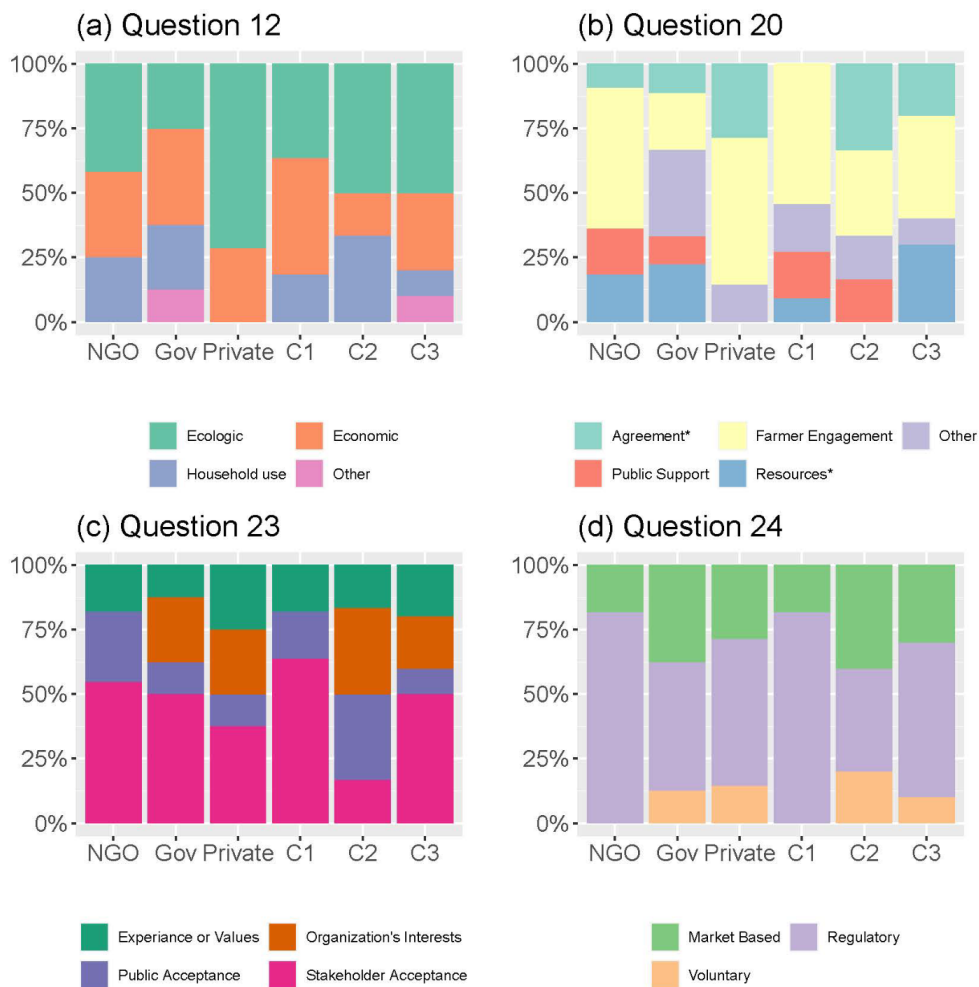
Figure 2. Stacked bar charts showing interviewees' highest-ranked options for questions 12, 20, 23, and 24. NGO, Gov, Private, C1, C2, and C3 represent the three stakeholder types and three values clusters. a) Question 12: Why do you think that Lake Erie is important to the region? b) question 20: what challenges do you think most impact the management of HABs in Lake Erie? Agreement*: Scientific agreement/ knowledge availability; Resources*: Resources for policy creation and enforcement; c) question 23: when considering a policy regarding water quality in Lake Erie, what is the most important consideration to your opinion?; d) question 24: what would be your preferred policy approach to addressing HABs in Lake Erie?

3.7 Network Analysis (RQ4)

Figure 3a displays the connections identified by our interviewees when asked who they worked with on Lake Erie HABs management in the last five years. Organizations with fewer connections directed towards them are peripheral nodes in the network, while those with more connections are central nodes. The network has 24 central network nodes (interviewees) and 121 total identified stakeholders. The distribution of stakeholder types represented in the network includes 47 NGOs, 32 private, and 40 government organizations. There are 551 connections listed, with an average of 23 connections reported by interviewees. The number of connections

ranged from 4 to 46 connections. Most peripheral organizations were typically small, locally-focused organizations, while the highly connected core organizations were often large national entities. For example, several of the peripheral organizations were local, city governments, and three of the top six connected organizations are involved in projects worldwide.

The organization with the most connections directed towards it in our map was an environmentally-focused nonprofit that operates in over 70 countries through multiple offices. They maintain hundreds of projects at a time, not all of which are water quality-oriented. Our second most connected organization was an Ohio-based environmental advocacy group that often works with policymakers and other stakeholders as part of their mission. Our third most connected organization was a well-established academic institution located in Ohio that often utilizes a lab for collaborative HABs research.

Figure 3b shows the density of organization connections stated by interviewees. The average number of connections was 5 over a range of 0 to 21. The distribution of connections was strongly skewed, with a small number of highly connected core organizations. The NGO stakeholder type had the broadest range of connections per organization (1-21), and they were present in the most connection levels out of any other stakeholder type. Five of the six most connected organizations were within the NGO stakeholder type. The government and private stakeholder types had similar ranges of connections (0-13 and 0-12, respectively).

Table 1 displays both the expected and observed EI homophily index values for each stakeholder type. We expected the network to be heterophilic if all possible connections were established. The private stakeholder type varied the most from its expected value of 0.471 for an index value of 0.647, displaying more heterophily than expected. The NGO and government stakeholder types were relatively similar to their expected index values, with NGOs slightly more homophilic than expected.
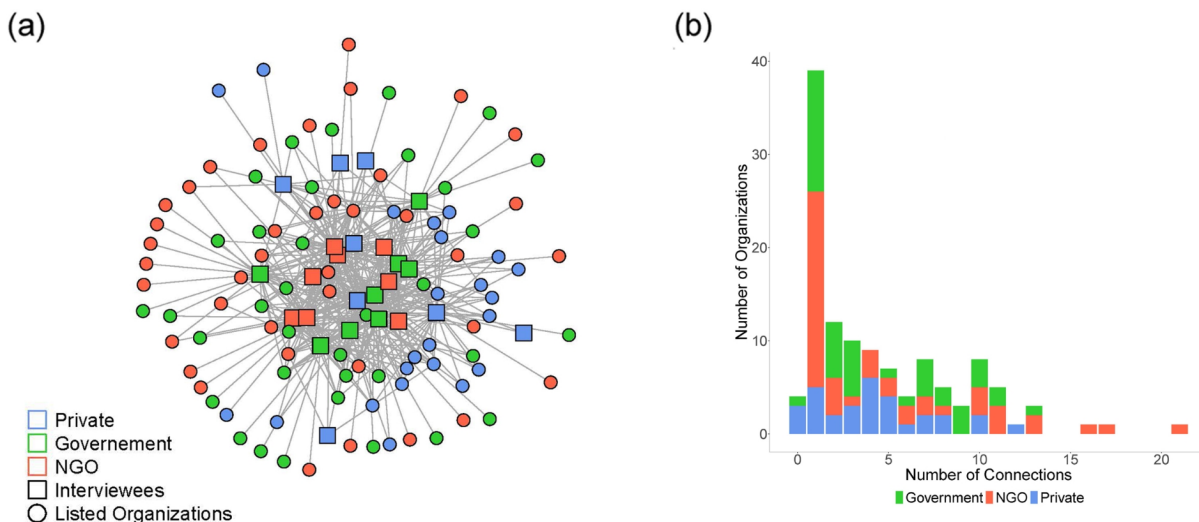

(a)

Private
Governement
NGO
Interviewees
Listed Organizations

(b)

Figure 3. a) Network map of stakeholders involved in western Lake Erie HABs management. Each square/circle represents an organization, and the grey lines represent the connections between them; b) network density stacked bar chart.

Table 1. Homophily index values table for each stakeholder type.

Sector	Expected	Observed
NGO	0.223	0.200
Private	0.471	0.647
Government	0.306	0.309

4 Final wrap up

This study shows that stakeholder types were not good predictors of values and policy preferences, but the interviewees themselves bring with them distinct sets of values, attitudes, and policy preferences. Stakeholders can be described as distinct clusters based on their values, and these clusters are associated with different policy preferences. Interviewees generally agreed that regulatory approaches would be the most effective, but the interviewees who disagreed had firm opinions on why regulatory approaches would not work. Other stakeholders recognize stakeholders' adversity to regulatory approaches as a challenge to policy change. A majority of the interviewees who found regulatory approaches to be the most effective said they likely wouldn't be feasible to implement. Although the stakeholders recognized this lack of feasibility, they still did not rank scientific agreement/knowledge availability as a strong barrier for HABs management. The different opinions and preferences of each interviewee may complicate the decision-making process. When considering beliefs and preferences in the decision-making process, when individuals with diverse backgrounds agree, there is a higher possibility the group will productively decide on a solution (Goethals & Nelson, 1973).

Although stakeholders may have different opinions on managing HABs best, there is an agreement on Lake Erie's significance as a regional resource, the complexity of HABs management, and the need for immediate action. Understanding Lake Erie's importance led to H2Ohio and other management plans (H2Ohio, 2019). A diverse group of stakeholders was involved in establishing H2Ohio, and many of the interviewees from the Ohio Watershed were hopeful the plan would be successful. While most interviewees supported regulatory programs, there was a tendency to keep the current voluntary programs as regulatory approaches did not seem feasible. "Feasibility just depends on having the political will and the money to implement; that's what's keeping a lot of these practices from being implemented." The easiest way to implement a collaborative approach would be to start with voluntary approaches and work towards adding any regulatory approaches that would be feasible.

Our network analysis reflects the current state of the governance and collaborative management of the watershed. Since the stakeholder types tend to be more heterophilic, there seems to be a willingness to work with various stakeholders. The top-connected stakeholders

were all larger organizations, while the least connected were smaller organizations. Although the larger organizations had more connections, smaller organizations were still connected and involved in the network. As more stakeholders become involved and active in the watershed, their connectedness should also increase.

5 Recommendations and future research

Our network analysis shows the potential for widespread, efficient collaboration and communication. Understanding the nature of these connections and the extent to which they enhance action will require a separate survey on the usage of connections to all stakeholders in the watershed. These independent surveys could include analyzing the data based on the subgroups to our established stakeholder types such as researchers and nonprofits. It could also include interviewing residents of the watershed and the general public on their views and willingness to be involved in the management process. Using surveys to expand upon the established connections would allow future researchers to find the network gaps that may cause unproductive management of HABs in Lake Erie.

Literature Cited

Allinger, L.E., Reavie, E.D., 2013. The ecological history of Lake Erie as recorded by the phytoplankton community. Journal of Great Lakes Research 39, 365-382.

Anderson, C.R., Berdalet, E., Kudela, R.M., Cusack, C.K., Silke, J., O'Rourke, E., Dugan, D., McCammon, M., Newton, J.A., Moore, S.K., 2019. Scaling up from regional case studies to a global harmful algal bloom observing system. Frontiers in Marine Science 6, 250.

Baker, D., Confesor, R., Ewing, D., Johnson, L., Kramer, J., Merryfield, B., 2014. Phosphorus loading to Lake Erie from the Maumee, Sandusky and Cuyahoga rivers: The importance of bioavailability. Journal of Great Lakes Research 40, 502-517.

Berardo, R., Turner, V.K., Rice, S., 2019. Systemic coordination and the problem of seasonal harmful algal blooms in Lake Erie. Ecology and Society 24.

Bingham, M., Kinnell, J., 2020. The Tourism Impacts of Lake Erie Hazardous Algal Blooms, Inland Waters-Dynamics and Ecology. IntechOpen.

Chaffin, J.D., Davis, T.W., Smith, D.J., Baer, M.M., Dick, G.J., 2018. Interactions between nitrogen form, loading rate, and light intensity on Microcystis and Planktothrix growth and microcystin production. Harmful Algae 73, 84-97.

Csardi, G., Nepusz, T., 2006. The igraph software package for complex network research. InterJournal, Complex Systems 1695, 1-9.

Dai, G.Z., Shang, J.L., Qiu, B.S., 2012. Ammonia may play an important role in the succession of cyanobacterial blooms and the distribution of common algal species in shallow freshwater lakes. Global Change Biology 18, 1571-1581.

De Pinto, J.V., Young, T.C., McIlroy, L.M., 1986. Great Lakes water quality improvement. Environmental Science & Technology 20, 752-759.

Fritzsche, D., Oz, E., 2007. Personal values' influence on the ethical dimension of decision making. Journal of Business Ethics 75, 335-343.

Gill, D., Rowe, M., Joshi, S.J., 2018. Fishing in greener waters: understanding the impact of harmful algal blooms on Lake Erie anglers and the potential for adoption of a forecast model. Journal of Environmental Management 227, 248-255.

Goethals, G.R., Nelson, R.E., 1973. Similarity in the influence process: The belief-value distinction. Journal of Personality and Social Psychology 25, 117.

Guo, T., Gill, D., Johengen, T.H., Cardinale, B.L., 2019. What determines the public's support for water quality regulations to mitigate agricultural runoff? Environmental Science & Policy 101, 323-330.

H2Ohio, 2019. Phosphorus Reduction Impact. http://h2.ohio.gov/about-h2ohio/

Harke, M.J., Steffen, M.M., Gobler, C.J., Otten, T.G., Wilhelm, S.W., Wood, S.A., Paerl, H.W., 2016. A review of the global ecology, genomics, and biogeography of the toxic cyanobacterium, Microcystis spp. Harmful Algae 54, 4-20.

Henry, A.D., Lubell, M., McCoy, M., 2011. Belief systems and social capital as drivers of policy network structure: The case of California regional planning. Journal of Public Administration Research and Theory 21, 419-444.

Homer, P.M., Kahle, L.R., 1988. A structural equation test of the value-attitude-behavior hierarchy. Journal of Personality and Social Psychology 54, 638.

Hothorn, T., Hornik, K., Van De Wiel, M.A., Zeileis, A., 2006. A lego system for conditional inference. The American Statistician 60, 257-263.

IJC, 1972. Great Lakes Water Quality Agreement.

IJC, 1987. Revised Great Lakes Water Quality Agreement of 1978 as amended by protocol.

IJC, 2012. Great Lakes Water Quality Agreement.

IJC, 2014. A Balanced Diet for Lake Erie: Reducing Phosphorus Loadings and Harmful Algal Blooms. Retrieved from: https://legacyfiles.ijc.org/publications/2014%20IJC%20LEEP%20REPORT.pdf

Jarvie, H.P., Johnson, L.T., Sharpley, A.N., Smith, D.R., Baker, D.B., Bruulsema, T.W., Confesor, R., 2017. Increased soluble phosphorus loads to Lake Erie: Unintended consequences of conservation practices? Journal of Environmental Quality 46, 123-132.

Jetoo, S., Grover, V.I., Krantzberg, G., 2015. The Toledo drinking water advisory: suggested application of the water safety planning approach. Sustainability 7, 9787-9808.

Kalcic, M.M., Kirchhoff, C., Bosch, N., Muenich, R.L., Murray, M., Griffith Gardner, J., Scavia, D., 2016. Engaging stakeholders to define feasible and desirable agricultural conservation in western Lake Erie watersheds. Environmental Science & Technology 50, 8135-8145.

Kim, K., Mun, H., Shin, H., Park, S., Yu, C., Lee, J., Yoon, Y., Chung, H., Yun, H., Lee, K., 2020. Nitrogen stimulates Microcystis-dominated blooms more than phosphorus in river conditions that favor non-nitrogen-fixing genera. Environmental Science & Technology 54, 7185-7193.

Lizardo, O., 2021. Social Networks: An Introduction. Retrieved April 12, 2021, from Ucla.edu
  website: http://olizardo.bol.ucla.edu/classes/soc-111/textbook/_book/1-intro.html#intro

Newell, S.E., Davis, T.W., Johengen, T.H., Gossiaux, D., Burtner, A., Palladino, D., McCarthy,
  M.J., 2019. Reduced forms of nitrogen are a driver of non-nitrogen-fixing harmful
  cyanobacterial blooms and toxicity in Lake Erie. Harmful Algae 81, 86-93.

Ohio EPA, 2013. Ohio Lake Erie Phosphorus Task Force II Final Report. Retrieved from:
  https://www.epa.ohio.gov/portals/35/lakeerie/ptaskforce2/Task_Force_Report_October_2
  013.pdf

Pitas, N.A., Mowen, A.J., Mueller, J.T., Taff, B.D., Graefe, A., 2020. The role of values,
  ideologies, and attitudes in shaping public support for privatization in local park and
  recreation services. Journal of Leisure Research 51, 16-35.

R Core Team. 2020. R: A language and environment for statistical computing. R Foundation for
  Statistical Computing, Vienna, Austria. URL https://www.R-project.org/.

Ravlin, E.C., Meglino, B.M., 1987. Effect of values on perception and decision making: A study
  of alternative work values measures. Journal of Applied Psychology 72, 666.

Rissman, A.R., Carpenter, S.R., 2015. Progress on nonpoint pollution: barriers & opportunities.
  Daedalus 144, 35-47.

Robertson, D.M., & Saad, D. A., 2011. Nutrient Inputs to the Laurentian Great Lakes by Source
  and Watershed Estimated Using SPARROW Watershed Models. JAWRA Journal of the
  American Water Resources Association 47, 1011-1033.

Sayers, M.J., Grimm, A.G., Shuchman, R.A., Bosse, K.R., Fahnenstiel, G.L., Ruberg, S.A.,
  Leshkevich, G.A., 2019. Satellite monitoring of harmful algal blooms in the Western
  Basin of Lake Erie: A 20-year time-series. Journal of Great Lakes Research 45, 508-521.

Scavia, D., DePinto, J.V., Bertani, I., 2016. A multi-model approach to evaluating target
  phosphorus loads for Lake Erie. Journal of Great Lakes Research 42, 1139-1150.

Schwartz, S.H., 2012. Unit 2 Theoretical and Methodological Issues Subunit 1 Conceptual Issues
  in. Psychol Cult Artic [Internet] 11, 12-13.

Smith, D.R., King, K.W., Williams, M.R., 2015. What is causing the harmful algal blooms in
  Lake Erie? Journal of Soil and Water Conservation 70, 27A-29A.

Smith, R.B., Bass, B., Sawyer, D., Depew, D., Watson, S.B., 2019. Estimating the economic
  costs of algal blooms in the Canadian Lake Erie Basin. Harmful Algae 87, 101624.

Stow, C.A., Glassner-Shwayder, K., Lee, D., Wang, L., Arhonditsis, G., DePinto, J.V., Twiss,
  M.R., 2020. Lake Erie phosphorus targets: An imperative for active adaptive
  management. Journal of Great Lakes Research 46, 672-676.

U.S. EPA. 2018. U.S. Action Plan for Lake Erie. Retrieved from:
  https://www.epa.gov/sites/production/files/2018-03/documents/us_dap_final_march_1.pd
  f

U.S. EPA. 2004. Lake Erie Lakewide Management Plan.

Vaske, J.J., Donnelly, M.P., 1999. A value-attitude-behavior model predicting wildland
  preservation voting intentions. Society & Natural Resources 12, 523-537.

Vliet, O.V., Hanger, S., Nikas, A., Spijker, E., Lieu, J., 2020. The importance of stakeholders in scoping risk assessments—Lessons from low-carbon transitions. Environmental Innovation and Societal Transitions 35.

Watson, S.B., Miller, C., Arhonditsis, G., Boyer, G.L., Carmichael, W., Charlton, M.N., Confesor, R., Depew, D.C., Höök, T.O., Ludsin, S.A., 2016. The re-eutrophication of Lake Erie: Harmful algal blooms and hypoxia. Harmful Algae 56, 44-66.

Watson, S.B., Ridal, J., Boyer, G.L., 2008. Taste and odour and cyanobacterial toxins: impairment, prediction, and management in the Great Lakes. Canadian Journal of Fisheries and Aquatic Sciences 65, 1779-1796.

Wilson, R.S., Beetstra, M.A., Reutter, J.M., Hesse, G., Fussell, D.V., Johnson, L.T., King, K.W., Labarge, G.A., Martin, J.F., Winslow, C., 2019. Commentary: Achieving phosphorus reduction targets for Lake Erie. Journal of Great Lakes Research 45, 4-11.

Wolf, D., Georgic, W., Klaiber, H.A., 2017. Reeling in the damages: Harmful algal blooms' impact on Lake Erie's recreational fishing industry. Journal of Environmental Management 199, 148-157.

Appendix A.

1. WLE dataset: WLEdataset
2. NLA dataset: NLAdataset
3. Code for model building

read and transform the data for both datasets
```{r}
library(standardize)
library(robustHD)

Weekly <- read.table("D:/RStudio/Weekly/Weekly_Aug4.csv", header = TRUE, fill = TRUE, sep = ",", quote = "")
Weekly$Year<-as.factor(Weekly$Year)
Weekly$Site<-as.factor(Weekly$Site)
Weekly$Season<-as.factor(Weekly$Season)
Weekly$Month<-as.factor(Weekly$Month)
Weekly_log<-Weekly
Weekly_log$ChlorophyllA<-log(Weekly$ChlorophyllA)
Weekly_log$Phycocyanin<-log(Weekly$Phycocyanin)
Weekly_log$TotalN<-log(Weekly$TotalN)
Weekly_log$TotalP<-log(Weekly$TotalP)
Weekly_log$Turbidity<-log(Weekly$Turbidity)
Weekly_log$Conductivity<-log(Weekly$Conductivity)
Weekly_log<-na.omit(Weekly_log)
Weekly_log$Temperature<-standardize(Weekly_log$Temperature)
Weekly_log$Microcystin_0.3[Weekly_log$Microcystin>0.3]<-1
Weekly_log$Microcystin_0.3[Weekly_log$Microcystin<=0.3]<-0
Weekly_log$Microcystin_1.6[Weekly_log$Microcystin>1.6]<-1
Weekly_log$Microcystin_1.6[Weekly_log$Microcystin<=1.6]<-0
Weekly_log$Microcystin_8[Weekly_log$Microcystin>8]<-1
Weekly_log$Microcystin_8[Weekly_log$Microcystin<=8]<-0

NLA <- read.table("D:/RStudio/NLA/NLA_Nov29.csv", header = TRUE, fill = TRUE, sep = ",", quote = "")
NLA$YEAR<-as.factor(NLA$YEAR)
NLA$WSA_ECO9<-as.factor(NLA$WSA_ECO9)
NLA$LAKENAME<-as.factor(NLA$LAKENAME)
NLA_log<-NLA
NLA_log$CHLA<-log(NLA$CHLA)
NLA_log$CYANO_BIOVOLUME<-log(NLA_log$CYANO_BIOVOLUME)
NLA_log$PTL<-log(NLA_log$PTL)
```

```
NLA_log$NTL<-log(NLA_log$NTL)
NLA_log$TURB<-log(NLA_log$TURB)
NLA_log$COND<-log(NLA_log$COND)
NLA_log<-na.omit(NLA_log)
NLA_log$TEMP<-standardize(NLA_log$TEMP)
NLA_log$LAT<-standardize(NLA_log$LAT)
NLA_log$MCYST_0.3[NLA_log$MCYST>0.3]<-1
NLA_log$MCYST_0.3[NLA_log$MCYST<=0.3]<-0
NLA_log$MCYST_1.6[NLA_log$MCYST>1.6]<-1
NLA_log$MCYST_1.6[NLA_log$MCYST<=1.6]<-0
NLA_log$MCYST_8[NLA_log$MCYST>8]<-1
NLA_log$MCYST_8[NLA_log$MCYST<=8]<-0
```
```

# set the prior for both datasets models
```{r}
prior1<-prior(normal(0,5),class=b)
```


#building models
```{r}
library(rstan)
library(brms)

#WLE
npmodel<-bf(TotalN~TotalP + (1 + TotalP |a| Year) + (1 + TotalP |b| Month) + (1 + TotalP |c| Site)) +gaussian()

fit_chl_26s_bigmodel<-bf(PChlorophyllA ~TotalP + TotalN + Temperature + Conductivity + (1 +TotalP +TotalN + Temperature + Conductivity|a|Year) + (1+TotalP +TotalN|b|Month) +(1+TotalP + TotalN +Conductivity|c|Site))
fit_chl_26s_NP<-brm(fit_chl_26s_bigmodel+npmodel+set_rescor(FALSE) ,data=Weekly_log, warmup=3000, iter=7000, prior=prior1, cores=4, sample_prior=TRUE, file="fit_chl_26s_NP_i",control=list(adapt_delta=0.99,max_treedepth=15),save_all_pars=TRUE , thin=2)
fit_phy_30s_bigmodel<-bf(Phycocynin~TotalP+TotalN+Temperature+Conductivity+(1+TotalP+ TotalN+Temperature+Conductivity|a|Year)+(1+TotalN+Conductivity|b|Month)+(1+TotalP+Total N|c|Site))
fit_phy_30s_NP<-brm(fit_phy_30s_bigmodel+npmodel+set_rescor(FALSE) ,data=Weekly_log, warmup=3000, iter=7000, prior=prior1, cores=4, sample_prior=TRUE,
```

```
file="fit_phy_30s_NP_i",control=list(adapt_delta=0.99,max_treedepth=15),save_all_pars=TRU
E, thin=2)
fit_mic_0.3_32s_bigmodel<-bf(Microcystin_0.3~TotalP+TotalN+Temperature+Conductivity+(1
+TotalP+TotalN+Temperature+Conductivity|a|Year)+(1+TotalP+TotalN+Conductivity|b|Month)
+(1+TotalP+TotalN|c|Site))+bernoulli()
fit_mic_0.3_32s_NP<-brm(fit_mic_0.3_32s_bigmodel+ npmodel+set_rescor(FALSE)
,data=Weekly_log, warmup=3000, iter=7000, prior=prior1, cores=4, sample_prior=TRUE,
file="fit_mic_0.3_32s_NP_i",control=list(adapt_delta=0.99,max_treedepth=15),save_all_pars=T
RUE, thin=2)
fit_mic_1.6_32s_bigmodel<-bf(Microcystin_1.6~TotalP+TotalN+Temperature+Conductivity+(1
+TotalP+TotalN+Temperature+Conductivity|a|Year)+(1+TotalP+TotalN+Conductivity|b|Month)
+(1+TotalP+TotalN|c|Site))+bernoulli()
fit_mic_1.6_32s_NP<-brm(fit_mic_1.6_32s_bigmodel + npmodel+set_rescor(FALSE)
,data=Weekly_log, warmup=3000, iter=7000, prior=prior1, cores=4, sample_prior=TRUE,
file="fit_mic_1.6_32s_NP_i",control=list(adapt_delta=0.99,max_treedepth=15),save_all_pars=T
RUE, thin=2)

#NLA
NPmodel<-bf(NTL ~ PTL + (1 + PTL | i | WSA_ECO9))+gaussian()

NLA_CHLA_16s_bigmodel<-bf(CHLA ~ PTL + NTL + TEMP  + COND + LAT + YEAR + (1
+ PTL + NTL + TEMP + COND + LAT |i| WSA_ECO9) + (1 | LAKENAME))
NLA_CHLA_16s_eco_NP<-brm(NLA_CHAL_16s_bigmodel+NPmodel+set_rescor(FALSE)
,data=NLA_log, warmup=3000, iter=7000, prior=prior1, cores=4, sample_prior=TRUE,
file="NLA_CHLA_16s_eco_NP_i", control=list(adapt_delta=0.99,
max_treedepth=15),save_all_pars=TRUE, thin=2)
NLA_CYANO_16s_bigmodel<-bf(CYANO_BIOVOLUME ~ PTL + NTL + TEMP + COND +
LAT + YEAR + (1 + PTL + NTL + TEMP + COND + LAT |  i | WSA_ECO9) + (1 |
LAKENAME))
NLA_CYANO_16s_eco_NP<-brm(NLA_CYANO_16s_bigmodel+NPmodel+set_rescor(FALSE
) ,data=NLA_log, warmup=3000, iter=7000, prior=prior1, cores=4, sample_prior=TRUE,
file="NLA_CYANO_16s_eco_NP_i", control=list(adapt_delta=0.99,
max_treedepth=15),save_all_pars=TRUE, thin=2)
NLA_MIC_0.3_16s_bigmodel<-bf(MCYST_0.3 ~ PTL + NTL + TEMP + COND + LAT +
YEAR + (1 + PTL + NTL + TEMP + COND + LAT | i | WSA_ECO9)  + (1 | LAKENAME))
NLA_MIC_0.3_16s_eco_NP<-brm(NLA_MIC_0.3_16s_bigmodel+NPmodel+set_rescor(FALS
E) ,data=NLA_log, warmup=3000, iter=7000, prior=prior1, cores=4, sample_prior=TRUE,
file="NLA_MIC_0.3_16s_eco_NP_i", control=list(adapt_delta=0.99,
max_treedepth=15),save_all_pars=TRUE, thin=2)
```

```
NLA_MIC_1.6_16s_bigmodel<-bf(MCYST_1.6 ~ PTL + NTL + TEMP + COND + LAT +
YEAR + (1 + PTL + NTL + TEMP + COND + LAT | i | WSA_ECO9) + (1 | LAKENAME))
NLA_MIC_1.6_16s_eco_NP<-brm(NLA_MIC_1.6_16s_bigmodel+NPmodel+set_rescor(FALS
E) ,data=NLA_log, warmup=3000, iter=7000, prior=prior1, cores=4, sample_prior=TRUE,
file="NLA_MIC_1.6_16s_eco_NP_i", control=list(adapt_delta=0.99,
max_treedepth=15),save_all_pars=TRUE, thin=2)
```

Appendix B.
1. Interview guide: InterviewQuestions
2. Ranking questions data: NumericalData
3. Nvivo Code Book: codebook

Questions in Components 1 and 2
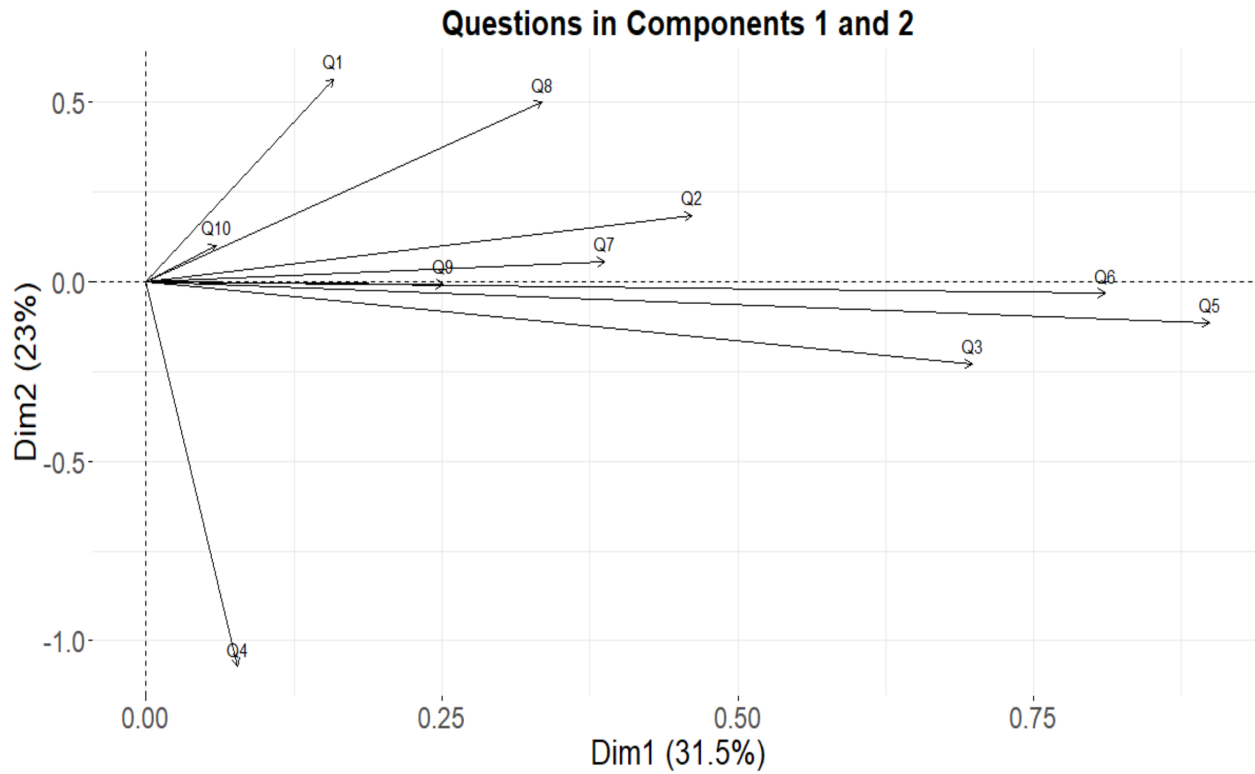
4. Components that make up the cluster analysis X-axis and Y-axis. Arrows that are more horizontal influence the X-axis while the vertical ones influence the Y-axis. The longer the arrow, the more impact the question had on the axis.