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Variability of summer cyanobacteria abundance: can season-ahead forecasts improve beach management?

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ABSTRACT

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As anthropogenic eutrophication and the associated increase of cyanobacteria continue to plague inland waterbodies, local officials are seeking novel methods to proactively manage water resources. Cyanobacteria are of particular concern to health officials due to their ability to produce dangerous hepatotoxins and neurotoxins, which can threaten waterbodies for recreational and drinking-water purposes. Presently, however, there is no cyanobacteria outlook that can provide advance warning of a potential threat at the seasonal time scale. In this study, a statistical model is developed utilizing local and global scale season-ahead hydroclimatic predictors to evaluate the potential for informative cyanobacteria biomass and associated beach closure forecasts across the June–August season for a eutrophic lake in Wisconsin (United States). This model is developed as part of a subseasonal to seasonal cyanobacteria forecasting system to optimize lake management across the peak cyanobacteria season. Model skill is significant in comparison to June–August cyanobacteria observations (Pearson correlation coefficient = 0.62, Heidke skill score = 0.38). The modeling framework proposed here demonstrates encouraging prediction skill and offers the possibility of advanced beach management applications.

KEYWORDS

Blue-green algae; cyanobacteria; Lake Mendota; season-ahead forecasting

Cyanobacteria represent some of the most ancient microorganisms on Earth, having appeared roughly 2.7 billion yr ago (Schirrmeister et al. 2013). In recent decades, accelerated nutrient input and widespread land cover change have resulted in a rapid expansion of harmful cyanobacteria in our coastal waters and inland lakes (Taranu et al. 2015). Cyanobacteria are photosynthetic bacteria that thrive in eutrophic waterbodies characterized by large influxes of nutrients. Cyanobacteria can form mats known as harmful algal blooms (HABs), triggering concern from health officials and water managers given their widely identified negative ecological, aesthetic, and socioeconomic implications (Dodds et al. 2013, Paerl 2017, Huisman et al. 2018). Importantly, common species of cyanobacteria (e.g., *Microcystis*) secrete hepato- and neurotoxins, threatening waterbodies used for recreation and drinking water (Taranu et al. 2012, Wynne

and Stumpf 2015). The negative impacts of HABs have received notable attention in larger waterbodies, such as Lake Erie. In 2014 Toledo, Ohio, was forced to issue a “do not drink” advisory when dangerous concentrations of cyanobacteria produced toxins in the public water supply (Bullerjahn et al. 2016). Widespread eutrophication, climate change, and an established relationship between algal biomass and nutrient input suggest that cyanobacteria pose a significant threat to small inland lakes, which have so far received less attention (Smith 2003, Paerl and Huisman 2008, Huisman et al. 2018).

Many meteorological, chemical, and biological variables influence cyanobacteria abundance, creating a complex, dynamic ecosystem (Stow et al. 1997, Hamilton et al. 2016). Additionally, each cyanobacteria community has its own unique characteristics, further complicating the understanding of how concurrent drivers collectively

impact cyanobacteria population in a lake (Soranno 1997, Taranu et al. 2012). For species commonly found in eutrophic dimictic lakes, key factors influencing overall abundance include temperature, water column stability, wind, nutrient availability, precipitation, atmospheric pressure, light transparency, and predatory grazing (Soranno 1997, Paerl 1988, Taranu et al. 2012, Ostfeld et al. 2015). Cyanobacteria abundance expresses notable intraseasonal variability, typically peaking during the summer season, and interannual variability (Lathrop and Carpenter 1992). Lake and beach managers, however, often have limited access to information indicating the expected intensity of cyanobacteria abundance ahead of the peak season for cyanobacteria productivity. Reactive management operations, in such cases, are used in determining recreational safety and beach closures. Advance notice of increased cyanobacteria abundance may allow lake and beach managers to alter cyanotoxin testing routines, train and inform lifeguards to watch for dangerous algae conditions, and launch public awareness campaigns before the high-risk season. Seasonal forecasts are intended to work in concert with shorter term forecasts (days to weeks), providing managers with information at several time scales. Providing decision makers with information on cyanobacteria conditions ahead of the high-risk season aims to extend an existing system of forecasts to improve overall management of cyanobacteria.

In recent decades, season-ahead forecasts have become a focus of research in many fields, with significant effort put toward predicting average or extreme precipitation, discharge, and temperature to inform operations in agriculture and reservoir management (Wood et al. 2005, Hansen et al. 2011). Forecasts at this scale typically aim to provide information characterizing the upcoming season, not a prescription of when events will occur. Many important management decisions fall into the gap between short-term and long-term forecasts. The development of forecasting systems at monthly and seasonal time scales can strengthen disaster preparedness by informing long-term contingency plans and activating short-term early warning systems (Vitart et al. 2012). In contrast to water quantity, relatively

little attention has been devoted to season-ahead prediction of water quality.

Currently, several short-term cyanobacteria forecasts are available through entities such as the National Oceanic and Atmospheric Administration (NOAA) for the purpose of beach management (Kavanaugh et al. 2013). Forecasts are issued up to 5 d out, based on local meteorological conditions and high-resolution satellite imagery. A review of forecast and predictive models for cyanobacteria blooms found that most existing models operate on forecast horizons of less than one week, with very few extending beyond 30 d (Rousso et al. 2020). Existing season-ahead forecasts of cyanobacteria abundance have been developed with a focus on spring phosphorus loads (e.g., by NOAA Great Lakes Environmental Research Laboratory) primarily to determine necessary nutrient reductions for targeted local management plans (Stow et al. 1997, Obenour et al. 2014). Phosphorus is generally accepted as the limiting nutrient for cyanobacteria growth in freshwater systems and has received significant attention in seasonal forecasting due to the importance of phosphorus management in many watersheds (Schindler 1977, Lathrop et al. 1998, Downing et al. 2001, Smith 2003). The abundance of cyanobacteria, however, is controlled by the dynamic state and reactions of many physical, chemical, and biological variables during both the prior and concurrent seasons, creating a complex array of ecosystem processes (Ostfeld et al. 2015, Zhu et al. 2019). Phosphorus is widely accepted as a driver of cyanobacteria productivity, and strong correlations between phosphorus load and cyanobacteria biomass have been demonstrated (Smith 1985, Stow et al. 1997, Lathrop et al. 1998). Local hydroclimatic processes, such as extreme rain events and river discharge, may influence phosphorus loading during the spring (Carpenter et al. 2018). Spring and summer temperatures may also control cyanobacteria productivity through direct effects on photosynthetic capacity, influencing competition with other photosynthetic organisms (Taranu et al. 2012). Therefore, consideration of season-ahead, local and large-scale hydroclimatic drivers may have potential to

improve the skill of season-ahead cyanobacteria forecasts.

The application of season-ahead forecasts to beach management allows for the investigation of season-ahead, nonanthropogenic drivers of cyanobacteria abundance. Incorporation of hydroclimatic (e.g., nonmanageable) variables may allow for skillful forecasts of cyanobacteria abundance at seasonal time scales. The focus of this article is to build and assess the skill of season-ahead cyanobacteria abundance forecasts conditioned on local and global scale hydroclimatic predictors, and the subsequent ability of seasonal forecasts to predict beach closings.

Study site

With the University of Wisconsin–Madison on its southern shore, Lake Mendota in Madison, Wisconsin (Fig. 1), is one of the most studied ecosystems on the planet (Carpenter et al. 2006, Lathrop 2007). The lake covers roughly 40 km² and is the first of 4 lakes in the Yahara river basin. The 596 km² Mendota watershed is 21%

urban and 53% agricultural (Genskow and Betz 2012). Mendota has a long history of eutrophication dating back to the 1940s, although anecdotal evidence of cyanobacteria blooms can be found as early as the 1880s (Lathrop 2007). From the 1940s until the 1970s, high nutrient concentrations were fueled by municipal wastewater discharge; however, Lake Mendota remains highly eutrophic to this day due to agricultural and urban development (Lathrop et al. 1998). Today, most nutrient conveyance is the result of manure application in the upper part of the Yahara watershed (Genskow and Betz 2012). Nutrient concentrations have been the focus of multiple cyanobacteria prediction models on Lake Mendota. An existing prediction model, developed by Stow et al. (1997), applied spring center-of-lake phosphorus to predict summertime cyanobacteria biovolume, with some success. Additionally, Lake Mendota was included in a Bayesian network model developed to assess the influence of short-term (1–2 weeks) nutrient concentrations (nitrogen and phosphorus) and climatic variables (air temperature, sunlight, and

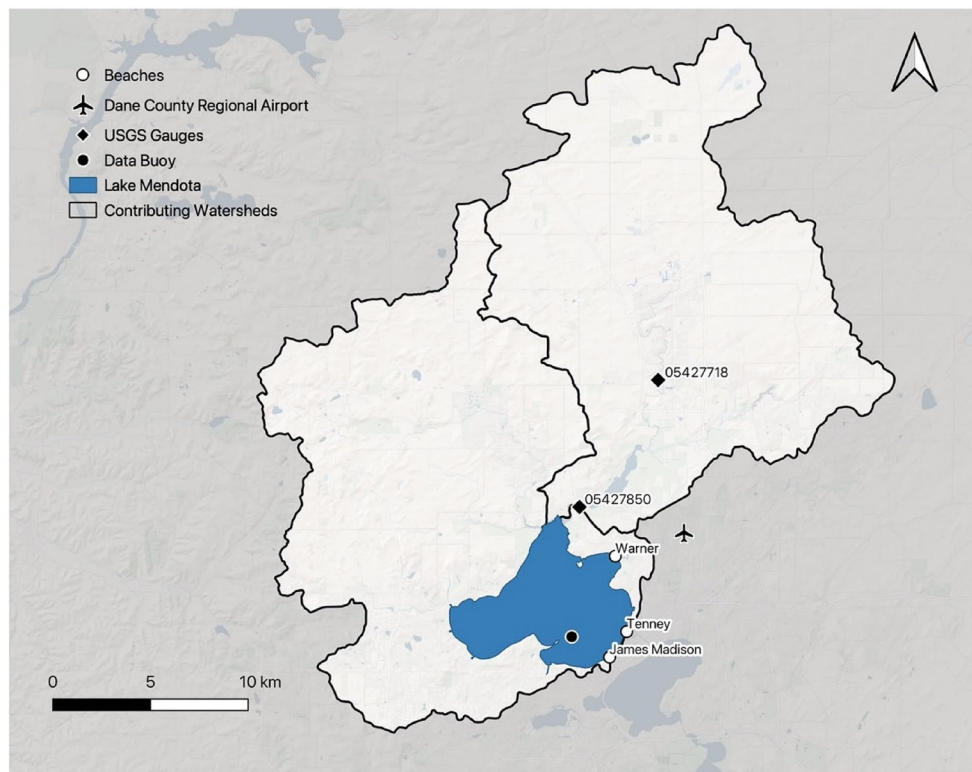


Figure 1. Lake Mendota and the Mendota watershed with select beaches, USGS gauges, and the North Temperate Lakes Long-Term Ecological Research (NTL-LTER) data buoy indicated (base map: Carto, watershed: WI DNR 2020, lake: City of Madison 2019).

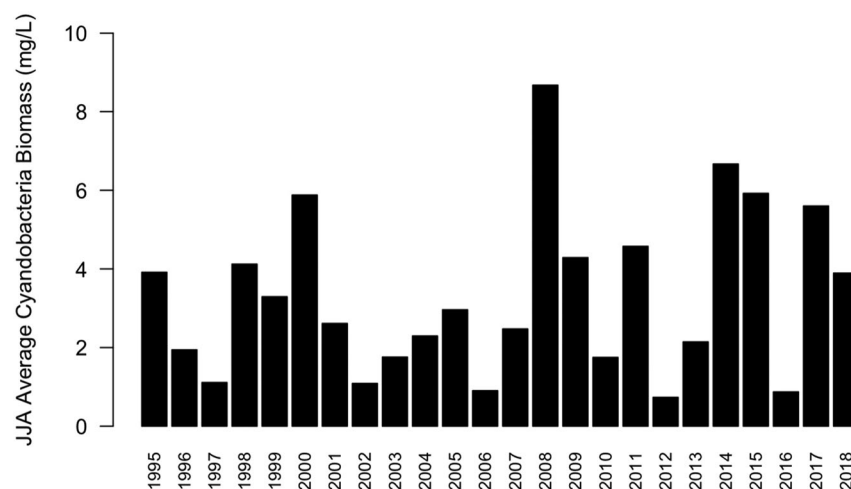


Figure 2. June–Aug (JJA) average cyanobacteria biomass for 1995–2018 measured at the NTL-LTER buoy in Lake Mendota (see Fig. 1 for location).

wind speed) on the probability of cyanobacteria blooms (Rigosi et al. 2015). To build on these efforts, the forecast presented here investigates the influence of local and global hydrologic and climatic drivers of cyanobacteria biomass at a seasonal time scale and creates a tool for proactive lake and beach management. This forecast works in concert with a subseasonal forecasting model for July–August cyanobacteria abundance, developed by Beal et al. (2021). Cyanobacteria prediction modeling at both the seasonal and subseasonal time scale allows for the consideration of both preseason (Mar–May) and within-season (Jun) drivers of productivity and provides lake managers with 2 opportunities to adjust management strategies before cyanobacteria abundances peak for the summer. As the lake is a cornerstone of the Madison community, millions of dollars have been invested in water quality monitoring, offering a uniquely rich dataset. Mendota is therefore well suited as a test case for the development, evaluation, and implementation of a season-ahead cyanobacteria forecasting system. Water quality data are available through the Northern Temperate Lakes Long-Term Ecological Research (NTL-LTER) database (Magnuson et al. 2020), and beach-closing data are available by request from the Madison–Dane County Public Health department (PHMDC 2020). Cyanobacteria abundance and associated beach closings typically peak across the June–August (JJA) summer season, with the greatest abundances typically occurring between July and

August. The forecast developed here addresses average summertime (Jun–Aug) cyanobacteria biomass to inform lake and beach management decisions at the beginning of the peak season for cyanobacteria productivity (Fig. 2).

Materials and methods

Forecasting models for July–August cyanobacteria biomass and beach closings are built and validated from 1995 to 2018 (24 yr) and 2005 to 2020 (16 yr), respectively. In the following *Local scale* and *Global scale* subsections, a literature review is conducted to identify potential preseason drivers of summertime cyanobacteria abundance. Predictors should be based on readily available preseason (Mar–May, MAM) observations to facilitate real-time predictions and must be significantly correlated (95% confidence level) with June–August (JJA) cyanobacteria biomass and beach closings. The subsection *Model construction* describes a principal component regression modeling approach, and metrics to quantify model skill are defined in the subsection *Model performance metrics*.

To compute biomass, biovolume was initially calculated for each species by multiplying the average cell volume for the geometric solid by the cell density in the water sample and then converting mm^3/mL of biovolume to mg/L of biomass. To describe seasonal beach closings, 2 separate metrics were developed: beach days closed (number of days a beach is closed during

a single JJA season due to cyanobacteria; Fig. 3), and beach periods closed (number of periods a beach is closed during a single JJA season, defined as one or more consecutive days closed, Fig. 4). Together, these 2 metrics better define the distribution of beach closings across the season by detailing the total number of days closed and how those days are grouped throughout the season. The suite of potential predictors includes persistent large-scale climate variables

and local spring drivers of cyanobacteria. Similar predictors were assessed for the cyanobacteria biomass model and beach closing model; however, both models were not required to retain the same set of predictors. Expanding the suite of predictors beyond springtime phosphorus allows for evaluation against a previous season-ahead prediction cyanobacteria prediction model on Lake Mendota developed by Stow et al. (1997).

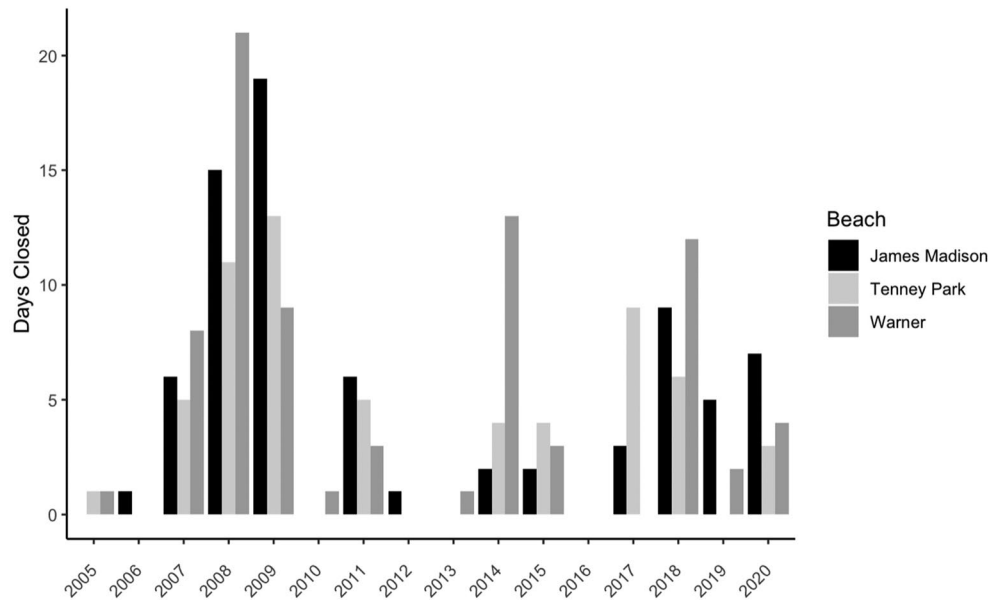


Figure 3. Jun–Aug (JJA) beach days closed due to cyanobacteria abundance (data courtesy of Madison–Dane County Public Health) for 2005–2020.

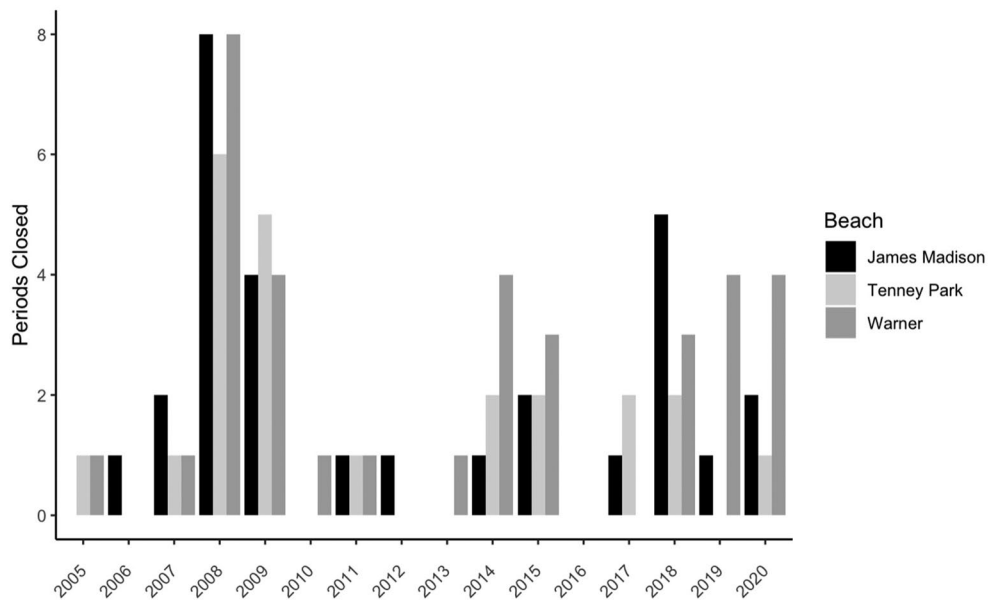


Figure 4. Jun–Aug (JJA) beach periods closed due to cyanobacteria abundance (data courtesy of Madison–Dane County Public Health) for 2005–2020.

Local scale

Prospective local-scale spring drivers include residual (legacy) and external phosphorus loadings and meteorological variables, such as temperature and precipitation. Phosphorus is recognized as the driving nutrient for primary production in many lake ecosystems (Bennett et al. 1999, Paerl 2017), and the relationship between algal biomass and total phosphorus in the growing season is well established (Vollenweider 1970, Smith 1982). Specifically, existing prediction models for Lake Mendota have illustrated the predictive power of spring phosphorus concentrations on summer algae abundance (Stow et al. 1997, Lathrop et al. 1998). Spring phosphorus concentrations have also been used to predict algae abundance in other temperate waterbodies (Dillon and Rigler 1974, Stumpf et al. 2012, Obenour et al. 2014, Stumpf et al. 2016). Additionally, researchers have noted the influence of meteorological variables on cyanobacteria abundance, including springtime temperature and precipitation (Paerl and Huisman 2008, Reichwaldt and Ghadouani 2012, Stow et al. 2015).

Numerous studies have demonstrated that phosphorus and nitrogen are major limiting nutrients for algal growth in inland lake ecosystems (Edmondson and Lehman 1981, Carey et al. 2012, Paerl 2017); thus, springtime phosphorus and nitrogen loads were evaluated as potential predictors of summertime cyanobacteria abundance. Precipitation and discharge during the spring season are thought to impact cyanobacteria abundance through the conveyance of nutrients from the watershed. Large precipitation events can flush high concentrations of nutrients into lakes, spurring algae growth (Schueler 1987, Carpenter et al. 2018). Higher intensity storms increase discharge, and tend to transfer higher concentrations of nutrients than lower intensity storms and their associated flows (Reichwaldt and Ghadouani 2012). The intensity and frequency of springtime precipitation events affect the discharge loading concentration, distribution, and residence time of phosphorus within a lake, and further influence the overall availability of nutrients to cyanobacteria in the summer season (Reichwaldt and Ghadouani 2012, Stow et al.

2015, Paerl and Otten 2016). Therefore, total precipitation, extreme precipitation events (>40 mm/d), and discharge from March to May were considered as potential predictors of summertime cyanobacteria abundance. While total precipitation and number of extreme events are similar predictors, they represent distinct hydrologic phenomena. Total precipitation may better represent moisture conditions in the watershed compared to extreme precipitation, which may lead to large runoff and nutrient loading events. Precipitation data are taken from the Midwest Regional Climate Center, and phosphorus and discharge data are taken from the US Geological Survey (USGS gauges 05427718 and 05427850; Wuertz et al. 2018, USGS 2021a, 2021b).

Global scale

Large-scale atmospheric-oceanic climate variables may influence local cyanobacteria abundance through atmospheric teleconnections, which influence meteorological conditions over the watershed from year to year. Global sea surface temperatures (SST) and sea-level pressures (SLP) are representative of these teleconnections and are well established as drivers of precipitation and temperature on seasonal time scales by altering atmospheric flow (Trenberth and Caron 2000, Markowski and North 2003). Therefore, regions of SSTs and SLPs are examined as potential predictors. The El Niño Southern Oscillation (ENSO), an anomalous warming or cooling of SST in the equatorial Pacific Ocean, is perhaps the most well known and most studied oceanic-atmospheric climate phenomenon with global impacts (Ropelewski and Halpert 1986, Ropelewski and Halpert 1987, Sarachik and Cane 2010). In the upper Midwest, ENSO is associated with warmer and drier winters during El Niño phases (Legler et al. 1999, Smith et al. 1999, WICCI 2011, Midwestern Regional Climate Center 2016), contributing to lower antecedent soil moisture conditions. Although the summertime influence of ENSO in the Midwest is less pronounced, early summer months have been characterized as cooler and wetter than normal in El Niño years (Midwestern Regional Climate Center 2016), establishing conditions for higher

runoff and nutrient transport potential. Both global and ENSO-related SST predictors were therefore considered as predictors and were identified using gridded correlation maps. SST data are retrieved from the NCEP/NCAR reanalysis (NCEP/NWS/NOAA/USDC 1994). In addition to selecting regions that meet the 95% statistical significance level requirement, distinct teleconnections between oceanic-atmospheric regions and the upper Midwest United States must also exist. SSTs are particularly advantageous from a prediction perspective as they fluctuate slowly over time, often allowing anomalies to persist across seasons. Similarly, sea-level pressure is also evaluated globally.

Model construction

A principal component analysis (PCA) and regression modeling approach was selected to predict cyanobacteria abundance and beach closings. PCA decomposes a space-time random field—all potential season-ahead predictors in this case—and produces a set of orthogonal time patterns that include the dominant signals, or principal components (PCs), stemming from the original set of predictors (Von Storch and Zwiers 1999, Block et al. 2009). Additionally, PCA efficiently accounts for multicollinearity that may be present in the predictors, a common problem in linear regression. Typically, the first few PCs explain the majority of variance in the data. Kaiser's rule was adopted, which specifies retaining all PCs with eigenvalues greater than one (Kaiser 1960). The retained PCs are then applied as predictors in a multiple linear regression model to predict JJA average cyanobacteria biomass and beach closings (independently). Leave-one-out cross-validation was applied for a hindcast assessment across 1995–2017 to evaluate model skill. This PCA leave-one-out cross-validation model takes the general form of equation 1:

$$\hat{Y}_i = \alpha_i + \beta_1 PC1_i + \beta_2 PC2_i \dots + \beta_j PCj_i \quad (1)$$

where α_i is a fitted value, PCj_i represents the j th principal component calculated with the i -th year dropped, β_j is the fitted coefficient for the j th

principal component, and $\hat{Y}_i$ represents the predicted value for the i th year. To account for uncertainty, random deviates from the standard deviation of the prediction error are added to the model (median) prediction (Helsel and Hirsch 1995).

Model performance measures

To assess model performance, model results were compared with observations of cyanobacteria biomass and beach closings using 3 performance measures: Heidke skill score (HSS), ranked probability skill score (RPSS), and a hit-miss matrix. Pearson and Spearman correlation coefficients, forecast bias, and false alarm ratio (FAR) were also calculated for the cyanobacteria biomass forecast. Forecast bias is the ratio of how often a specific category is forecasted to how often the specific category is observed, with a value equal to one indicating an unbiased forecast and values greater than and less than one indicating overforecasting and underforecasting, respectively (Dee and Da Silva 1998). FAR is a simple ratio of the number of nonoccurrence forecasts of a specific category and the total number of times the specific category is forecasted. Values for this metric range from 0 to 1, where 0 indicates a perfect score (Schaefer 1990).

Both HSS (equation 1) and RPSS (equation 2) report the model's ability to predict categorical outputs (e.g., high vs. low) compared to a reference forecast, typically based on observed data (climatology). For hydroclimate prediction, a 3-category division is often adopted, with the reference forecast based on equal probability of categories (33% each; Block et al. 2009, Alexander et al. 2019, Lala et al. 2020). This approach was applied to the JJA average cyanobacteria biomass prediction for *below normal*, *near normal*, and *above normal* conditions, denoted as [B N A]. For beach days closed and beach periods closed, a 2-category division with *normal* ($x(i) \leq \text{mean}(\text{-closed})$) and *above normal* ($x(i) > \text{mean}(\text{closed})$) was adopted and denoted as [N A], where $x(i)$ represents the observed number of beach days closed in the i th year. The observational probabilities of each category are not equal in this case and are unique to each beach location.

The HSS takes the general form of equation 2:

$$\text{HSS} = \frac{\sum_i P(F_i, O_j) - \sum_i P(F_i)P(O_i)}{1 - \sum_i P(F_i)P(O_i)} \quad (2)$$

which describes forecast skill in terms of $i, j = [\text{B N A}]$. The joint distribution of forecasts and observations is described by $P(F_i, O_j)$ while the marginal distributions of forecasts and observations are described by $P(F_i)$ and $P(O_j)$, respectively (Wilks 2011). HSS values range from $-\infty$ to 1, where 0 represents no improvement over the reference forecast (climatology) and 1 represents a perfect forecast.

The RPSS measures forecast skill by accounting for the magnitude of error in the forecast, differentiating from HSS (Wilks 2011). For example, in the case of a [B N A] category forecast, if the *above normal* category is observed, RPSS would penalize a forecast that predicts *below normal* conditions more than a forecast that predicts *near normal* conditions. First, the ranked probability score (RPS) is calculated according to equation 3:

$$\text{RPS} = \frac{1}{n_{\text{cat}} - 1} \sum_{i_{\text{cat}}}^{n_{\text{cat}}} (P_{\text{cumfct}_{i_{\text{cat}}}} - P_{\text{cumobs}_{i_{\text{cat}}}})^2 \quad (3)$$

where n_{cat} is the number of forecast categories and i_{cat} is the category number. $P_{\text{cumfct}_{i_{\text{cat}}}}$ and $P_{\text{cumobs}_{i_{\text{cat}}}}$ are the cumulative probability vectors of the forecast and observation, respectively, for the specific category of interest. RPSS then compares the RPS of the forecast, RPS_{fct} to the RPS of climatology, RPS_{clim} , using equation 4:

$$\text{RPSS} = 1 - \frac{\text{RPS}_{\text{fct}}}{\text{RPS}_{\text{clim}}} \quad (4)$$

As with HSS, RPSS values range from $-\infty$ to 1, where 0 represents no skill and 1 represents a perfect forecast.

Results

Cyanobacteria biomass model

Both local and global scale variables are considered as potential predictors for JJA average cyanobacteria biomass. Local scale predictor variables meeting the established criteria include phosphorus loadings and discharge from the Yahara River at the mouth of Lake Mendota, total April precipitation, and precipitation events exceeding 40 mm/d from the Madison–Dane County regional airport (Table 1).

SST in the equatorial Pacific Ocean correlate strongly with Mendota's summertime (JJA) cyanobacteria biomass (Fig. 5), a region typically associated with ENSO. Xiao et al. (2019) found evidence for synchronization between phytoplankton dynamics and ENSO in northern Wisconsin lakes, suggesting that ENSO has some influence on local climatic conditions. Although other oceanic regions of statistically significant correlation between SST and summertime cyanobacteria abundance exist (Fig. 5), teleconnections between these regions and the upper Midwest are not overly apparent; therefore, the selection of SST is restricted to the equatorial Pacific Ocean.

Although phosphorus load meets the inclusion criteria for model development (correlation at the 95% confidence level), higher forecast skill is achieved without including phosphorus in the final suite of predictors. Thus, the final suite of season-ahead (Mar–May) predictors includes average discharge, the number of extreme precipitation events, total April precipitation, and

Table 1. Pearson and Spearman correlation coefficients between June and August (JJA) average cyanobacteria biomass and Mar–May (MAM) potential predictor variables (1995–1996, 1998–2017); asterisks indicate statistical significance at the 95% level (1 = 1995–2002 interpolated from upstream USGS station 05427718; 2 = 1995–2008 interpolated from upstream USGS station 05427718).

Cyanobacteria biomass predictors	Pearson	Spearman
MAM precipitation events >40 mm/d (MRCC)	0.58*	0.56*
Apr total precipitation (MRCC)	0.46*	0.44*
MAM average discharge (USGS Station 05427850) ¹	0.42*	0.39
MAM average SST in Equatorial Pacific (NOAA)	−0.44*	−0.45*
MAM average external phosphorus load (USGS Station 05427850) ²	0.38	0.48*

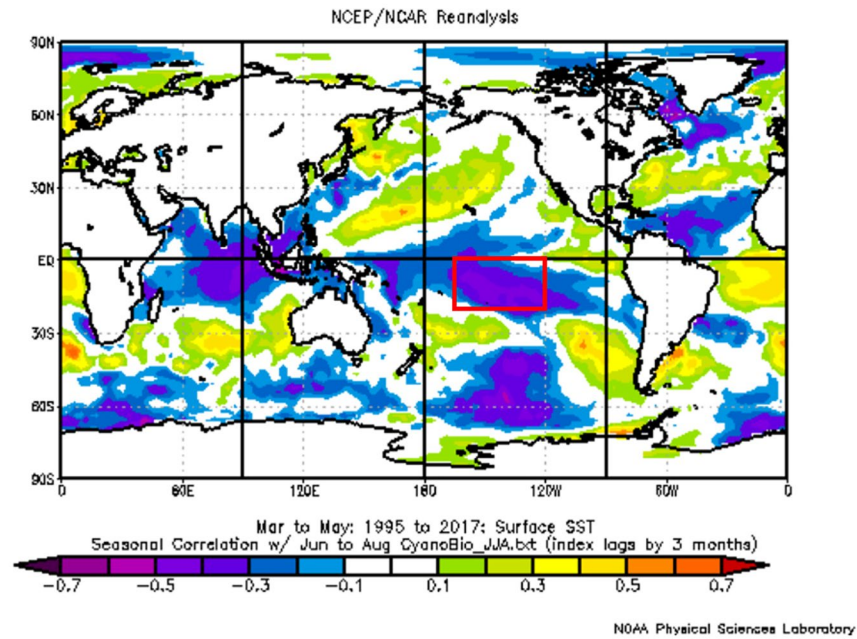


Figure 5. Correlation map of Mar–May (MAM) average SSTs and Jun–Aug (JJA) average cyanobacteria biomass; MAM average SSTs in the box (190W–120W, 0–20S) are selected as a potential predictor.

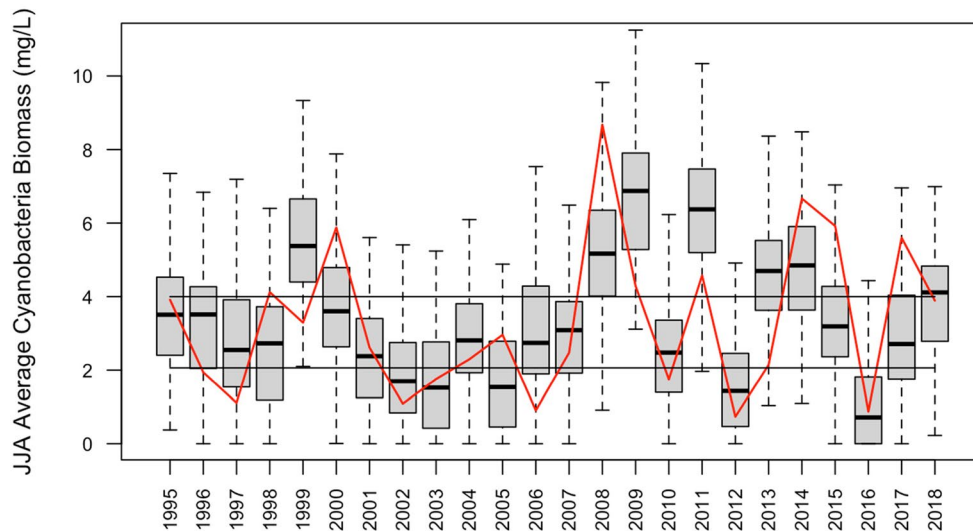


Figure 6. Time series of Jun–Aug (JJA) average cyanobacteria biomass observations (solid line) and predictions (boxes), with categories separated by horizontal black lines.

average SST in the equatorial Pacific Ocean. According to Kaiser's rule, only the first PC, explaining approximately 45% of the variance, is retained for inclusion in the prediction model. A cross-validated hindcast produces a Pearson correlation coefficient of 0.62 between median model outputs and observed cyanobacteria biomass, indicating moderate predictive skill (Fig. 6). This marks an improvement on previous Lake Mendota models. For example, the model developed by Stow et al. (1997) using spring

center-of-lake phosphorous as a predictor of summertime cyanobacteria—with the addition of data from 1995 to 2017—has a cross-validated Pearson correlation coefficient of 0.46.

The RPSS and HSS values based on categories of equal probability are 0.60 and 0.38, respectively, indicating improvement over climatology, and model ability to generally shift toward the appropriate category. The hit-miss matrix (Table 2) based on the [B N A] categorical divisions demonstrates high agreement; however,

there is a slight propensity toward predicting *near normal* conditions when *above* and *below normal* conditions are observed. Additionally, the hit-miss matrix (Table 2) and FAR and forecast bias (Table 3) all suggest that the model is slightly biased toward the *near normal* category. The model's ability to skillfully predict the *above normal* category—when cyanobacteria is most abundant and managers most concerned—is highly advantageous; however, the cyanobacteria peaks in 2008 and 2017 are clearly underpredicted. Both underpredictions may be related to the distribution of precipitation throughout the spring. While both 2008 and 2017 had high overall precipitation, many days did not actually surpass the 40 mm/d threshold and were thus not counted. Additionally, cyanobacteria biomass is substantially overpredicted in 2009 and 2013 even though the model average prediction is still in the appropriate category. Both years saw a relatively high number of extreme precipitation events and

increased streamflow. Furthermore, a limitation of the hydroclimatic forecasting approach for water quality variables is the difficulty in capturing food web dynamics, which play a significant role in structuring cyanobacteria communities in Lake Mendota (Kasprzak and Lathrop 1997, Walsh et al. 2017). Shifts in food web dynamics may have an influence on summertime cyanobacteria abundance that is not captured in the model.

Beach closings

Categorical forecast models for beach days closed and periods closed are developed for 3 beaches located along the eastern side of Lake Mendota (Fig. 1). Selected season-ahead predictors mirror those included in the cyanobacteria biomass model, including average discharge, P loading, the number of extreme precipitation events, and Pacific Ocean SST; however, positive correlations between number of days or periods closed and average discharge and extreme precipitation events were the only significant correlations at any of the beaches (Table 4). As with the cyanobacteria biomass model, only the first PC is retained for inclusion in each of the beach prediction models. Cross-validated hindcast model results for days and periods closed at each beach indicate moderate to strong model skill and an improvement over climatology in most metrics (Tables 5 and 6 for James Madison only).

Beach days closed tends to be more skillful than beach periods closed; however, performance metrics are highly sensitive to the short hindcast period and strongly influenced by data in single years. This limited number of data points is

Table 2. Hit-miss matrix for categorical Jun–Aug (JJA) average cyanobacteria biomass prediction and observations.

		Forecast		
		B	N	A
Observed	B	5	3	0
	N	2	4	2
	A	0	3	5

B = below normal, N = normal, A = above normal.

Table 3. Forecast bias and false alarm ratios for categorical JJA average cyanobacteria biomass predictions.

Category	Forecast bias	False alarm ratio (FAR)
B	0.88	0.29
N	1.25	0.6
A	0.88	0.29

B = below normal, N = normal, A = above normal.

Table 4. Pearson correlation coefficients between Jun–Aug (JJA) beach days/periods closed and Mar–May (MAM) potential predictor variables; asterisks indicate statistical significance at the 95% confidence level.

Beach closing predictors	Characteristic predicted	James Madison	Tenney	Warner
MAM precipitation events >40 mm/d (MRCC)	Days closed	0.75*	0.70*	0.69*
Apr precipitation (MRCC)		0.21	0.41	0.37
MAM average discharge (USGS Station 05427850)		0.65*	0.47	0.3
MAM average SST in Equatorial Pacific (NOAA)	Periods closed	−0.42	−0.43	−0.46
MAM average external phosphorus load (USGS Station 05427850)		0.39	0.32	0.39
MAM precipitation events > 40 mm/d (MRCC)		0.69*	0.87*	0.81*
Apr precipitation (MRCC)		0.29	0.42	0.26
MAM average discharge (USGS Station 05427850)		0.37	0.44	0.57*
MAM average SST in Equatorial Pacific (NOAA)		−0.42	−0.45	−0.36
MAM average external phosphorus load (USGS Station 05427850)		0.16	0.39	0.36

Table 5. Ranked probability skill scores (RPSS), Heidke skill scores (HSS), and Pearson correlations for beach days and periods closed prediction models for 3 Lake Mendota beaches.

Beach	Beach days closed			Beach periods closed		
	Median RPSS	HSS	Pearson correlation	Median RPSS	HSS	Pearson correlation
James Madison	0.81	0.49	0.65	0.25	0.35	0.36
Tenney	0.08	0.13	0.58	0.38	0.35	0.64
Warner	-0.01	0.21	0.31	0.69	0.49	0.66

Table 6. Hit-miss matrix for categorical beach days closed predictions and observations at James Madison beach.

		Forecast	
		N	A
Observed	N	6	3
	A	3	4

N=normal, A=above normal.

especially problematic for prediction in extreme years (e.g., 2013, Fig. 7). In the case of James Madison beach, predictors covary closely with the number of beach days closed except for 2013–2014 (Fig. 8). The days closed forecast results mirror the cyanobacteria abundance prediction in 2013, in that both were overpredicted, potentially resulting from changes in the food web not captured by the model. The model also overpredicts 2014, likely due to the elevated phosphorus levels; however, this may not have materialized in beach closures due to abnormally low discharge. Additionally, 2015 and 2017 above-average cyanobacteria abundance did not directly translate into above-average beach

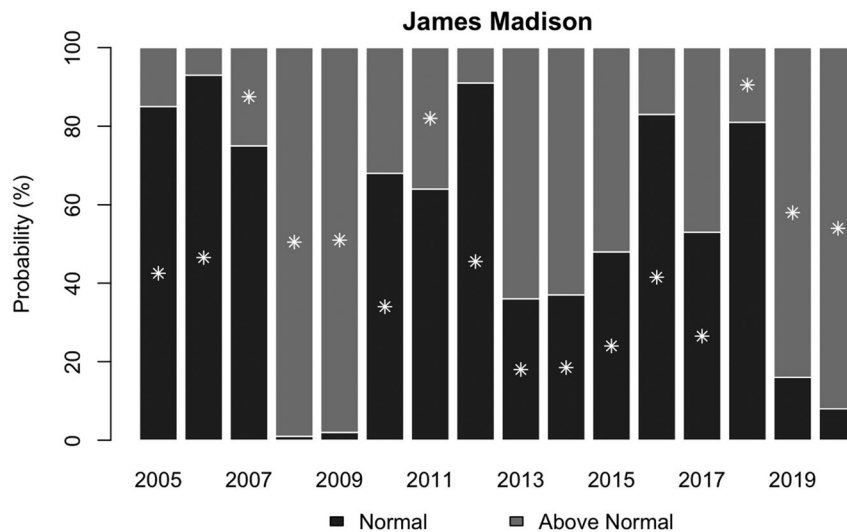


Figure 7. Bar chart representing probabilistic predictions of beach days closed at James Madison beach. Normal category includes 2 or fewer days closed; above normal refers to more than 2d closed per summer. The observed category is illustrated with a white star.

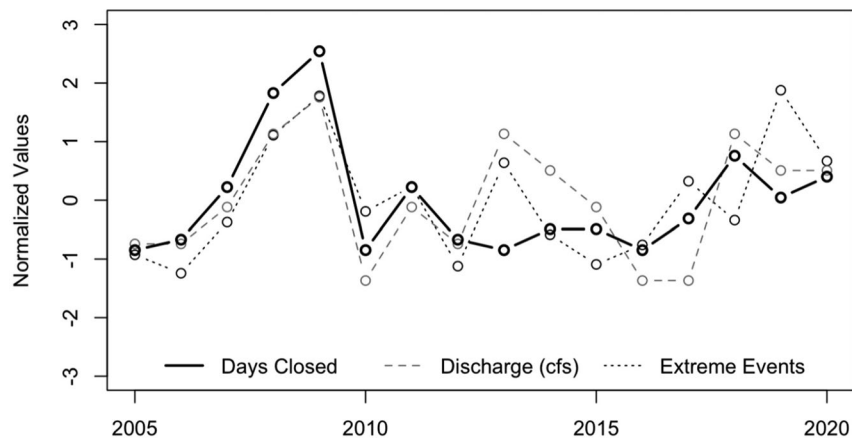


Figure 8. Time series of normalized predictors and beach days closed for James Madison beach.

closures. There are several factors that may be at play in this disconnect. Wind conditions, for example, have been shown to influence horizontal movement of surface algae (Deng et al. 2016), which may cause blooms to concentrate away from beaches, allowing them to stay open. In looking at specific years, there is expected variability due to the complex dynamics of this lacustrine ecosystem.

Discussion

The development and evaluation of prospective season-ahead prediction models for cyanobacteria biomass and beach closures, based on local and global scale predictors, are presented. The model is developed as part of a subseasonal to seasonal cyanobacteria forecasting system for Lake Mendota. Previous season-ahead prediction models have utilized phosphorus as the primary predictor variable, given its influence on cyanobacteria abundance and ability to be managed. Here, alternative predictors are also evaluated to better understand their potential contribution to prediction skill and ability to represent signals of phosphorus conveyance and distribution. In addition, models contingent solely on phosphorus data collection are subject to continuous sampling and processing lag times—often well beyond one season—which may serve as a major lake management disincentive. The modeling framework proposed here alleviates such dependence, demonstrating strong prediction skill. The proposed framework incorporates a larger suite of predictor variables than utilized in previous forecasts; however, the modeling approach remains straightforward—a clear strength for future applications. It should be noted that Lake Mendota has a wealth of high-quality, long-term data, which is uncommon among similar small inland lakes. Development of season-ahead forecasts for algae may benefit management practices in other lakes. While it is unlikely that nutrient loading and within-lake predictors will be as well characterized for other lakes, the hydroclimatic drivers evaluated here (e.g., precipitation, extreme precipitation events, air temperature, and sea surface temperatures) are widely available across the United States and may be used for forecasting applications in other lakes.

Although model performance exhibits predictive skill for cyanobacteria biomass, beach days closed, and beach periods closed, there are several noteworthy challenges. The statistical forecast models developed here are limited by the short time series available, with some inconsistencies in the ability to predict extremes. This may be addressed through calibrated physically based lake process models run in a predictive mode, potentially capturing complex dynamics across biological, chemical, and environmental processes; however, preliminary exploration has indicated poor to marginal skill for Lake Mendota. Another remaining challenge is when one category is predicted with high probability (confidence), yet observations fall in a different category (e.g., 2013, Fig. 7). This is different from moderate probability of being in the unobserved category and may be a challenge to resource managers. Relatedly, the thresholds between categories utilized here are subjective; however, selection does impact model performance. Individual managers are likely to have their own preferred thresholds, warranting further evaluation into model performance for specific choices.

As discussed previously, both temperature and phosphorus load are well established as drivers of cyanobacteria productivity; however, neither variable added predictive power at the seasonal scale. The Stow et al. (1997) prediction model uses April within-lake phosphorus concentrations to predict July–September cyanobacteria abundance with notable skill. Additionally, in the complementary subseasonal forecasting model for cyanobacteria abundance, June external phosphorus loads were highly correlated with July–August cyanobacteria abundance (Beal et al. 2021). It is possible that the temporal difference between the phosphorus predictor and summertime cyanobacteria biomass is responsible for this difference in skill. Internal phosphorus loading is also a significant source of phosphorus for Lake Mendota during the summer and is not accounted for in this set of predictors (Soranno et al. 1997).

Spring air temperatures have been shown to influence water temperature and summertime bloom onset (Zhang et al. 2016), prompting the

inclusion of spring air temperature as a potential predictor of summertime cyanobacteria biomass. Air temperature may have direct and indirect impacts on cyanobacteria abundance (Taranu et al. 2012). High temperatures (above 25 C) during the growing season generally promote cyanobacteria growth over phytoplankton species such as diatoms and green algae (Paerl and Huisman 2008). Higher air temperatures may indirectly favor cyanobacteria, given that increased temperatures promote stratification strength, allowing cyanobacteria to outcompete other algal groups by using specialized gas vacuoles to adjust their position in the water column (Jöhnk et al. 2008, Paerl and Huisman 2008). Additionally, water temperatures have been shown to control summertime cyanobacteria productivity in Lake Mendota (Konopka and Brock 1978); however, none of the temperature-based predictors investigated correlate at a statistically significant level with biomass. There may be several explanations for this: Researchers have noted that higher temperatures have a direct effect on the timing and proportional dominance of cyanobacteria, but not the amount of annual biomass (Wagner and Adrian 2009, Elliott 2012). While a causal relationship has been demonstrated between spring air temperatures and summertime cyanobacteria abundance in subtropical regions (Paerl and Huisman 2008, Deng et al. 2014, Zhang et al. 2016), that same relationship has not been shown to exist in the northern temperate climate of the study site. This could be due to the temporal mismatch of seasonal abundance with spring temperatures. While high spring temperatures may encourage cyanobacteria dominance, this does not necessarily imply long-term abundance (Anneville et al. 2015, Persaud et al. 2015, Zhang et al. 2016). Additionally, temperature fluctuations occurring in the spring are accompanied by a variety of additional environmental changes, complicating the direct cyanobacteria response to temperature (Konopka and Brock 1978). The simplicity of the temperature-based predictors proposed may not be capable of fully capturing the summer cyanobacteria biomass response to temperature nuances occurring throughout the season. Clearly, the predictor variables considered in this study may impact individual cyanobacteria

communities differently; however, average cyanobacteria biomass across all communities is specifically addressed here, as current management practices do not consider the presence of individual communities. Still, there is clear merit in the consideration of individual cyanobacteria communities that pose a greater toxicity risk, specifically those that have the potential to produce toxins, for future prediction efforts.

For this analysis, predictions are issued at the end of the spring season (beginning of June). This advance notice of summertime cyanobacteria conditions provides lake and beach managers with information necessary for making proactive management decisions ahead of the peak season for cyanobacteria productivity. These decisions may include changing the frequency of water quality testing, altering training and scheduling for lifeguards, tailoring public engagement strategies, and preparing emergency resources for recreators. Working with the sub-seasonal forecast developed by Beal et al. (2021), preseason and within-season (summer) predictions are issued for cyanobacteria abundance, allowing decision makers to adapt and optimize management strategies across the peak season for cyanobacteria productivity. The model developed here is a key component of this forecasting system, providing information on expected cyanobacteria abundances before recreational use of Lake Mendota begins to increase and toxin production becomes a potential public health threat. Linking seasonal and subseasonal cyanobacteria forecasts informs decisions at multiple time scales, allowing for an optimized approach to cyanobacteria management. Effectively implementing this forecasting system requires improved understanding of manager needs, key decisions dates, and available actions, all themes of ongoing research to facilitate how forecasts can better be integrated into lake and beach management.

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