J. Aquat. Plant Manage. 64(1): 13–24

Remote and field-based sensors for harmful algal bloom management: Literature review and expert input

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ABSTRACT

Managing harmful algal blooms (HABs) is increasingly complex given the diversity of nuisance algal issues and apparent stochastic nature of HAB distributions over space and time. While remote and field-based sensors (e.g., satellites, *in situ* sondes, autonomous sampling devices) have advanced HAB monitoring, uncertainty remains in how to integrate data for management decisions. This exploratory study reviewed literature on sensor use for HAB management and engaged experts in HAB management to identify data required for decision-making. Only 2.5% of reviewed studies (n = 199) reported remote and field-based sensors used directly for management. Of the few studies available, data were used to prioritize waterbodies potentially needing management, provide early warning systems to initiate more frequent monitoring prior to management, and evaluate effectiveness of management efforts. Expert input provided opinions, perceptions, and examples of how remote sensing and field-based sensor technologies may support HAB management (e.g., when, where, and what to manage and management effectiveness) and identified key data gaps to expand application. Emerging sensor technologies may be useful to identify HAB taxa and horizontal and vertical distribution in the water body. Applying sensor-based data requires integration with traditional methods, real-time use, improved data analysis tools, and clearer communication of uncertainty. As remote sensing and field-based sensor technologies advance, their role in the HAB management decision process will continue to expand, providing critical support for the protection of aquatic health and human safety.

Key words: automated, decision, HAB, satellite, sensing, sondes

INTRODUCTION

Over the past five decades, rapid advancements in remote and field-based sensor technologies have improved the monitoring or frequent spatial and temporal measurement of freshwater harmful algal blooms (HABs) (Binding et al. 2020; Khan et al. 2021; Johansen et al. 2023; Rolim et al. 2023). In this paper, remote sensors refer to devices to collect HAB data without physical contact with water (e.g., unmanned aircraft systems [UAS], fixed-wing planes, or spaceborne or satellite platforms), whereas field-based sensors involve devices that are in direct contact with the water, algae or cyanobacteria (e.g., *in situ* data sondes) and can be attached to autonomous vehicles (Johansen et al. 2023). Innovations in open-access satellite imagery, autonomous vehicles, optical sensors, and computational and software capabilities have made it possible to collect, analyze, and visualize data at increasingly finer spatial and temporal scales (Topp et al. 2020). While a decade ago, satellite imagery or derived map products required email distribution on a weekly or biweekly basis; (Jewett et al. 2008), today large-scale areas such as the Great Lakes can be monitored in near real time with online tools (Beaton et al. 2020; Woodcock et al. 2020). These advancements have led to quantifiable cost benefits for HAB monitoring programs and indicate that leveraging remote sensing can potentially provide estimated savings ranging from \$5.7 to \$316 million for U.S. lakes and reservoirs annually (Papenfus et al. 2020). With these impactful advancements in HAB monitoring, the next logical question is: how can remote sensing and field-based sensors be used to make actionable decisions to inform HAB management?

Freshwater HABs are generally defined as visible overgrowths of algae and cyanobacteria that can pose risks to human health, harm the environment, and impact local economies (CDC 2021; Christensen et al. 2024). HABs are increasingly posing threats to inland water resources (Brooks et al. 2016) because of greater incidence and severity of environmental hazards (e.g., droughts, hurricanes) (Paerl and Huisman 2009; Paerl and Paul 2012; Smucker et al. 2021), resulting in a need for monitoring to inform management. HAB management is defined as a biological, chemical, mechanical, or physical action to decrease risks or impairments to water uses. Scalable management technologies for HABs are available, and new technologies are being developed and tested, but because of the apparent stochastic nature of many planktonic blooms (Graham et al.

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DOI: 10.57257/JAPM-D-25-00001

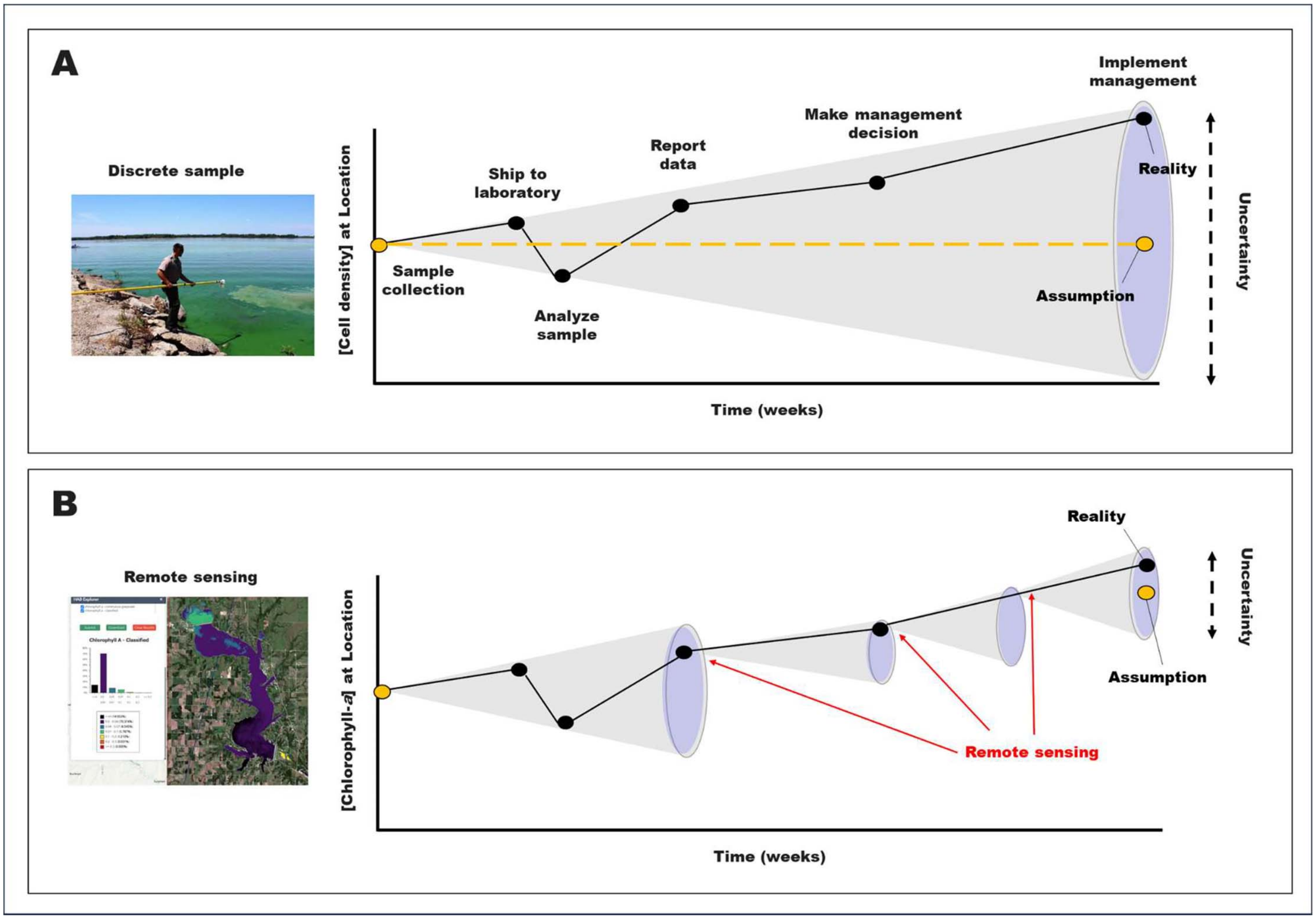

Figure 1. Conceptual representation of the decreased uncertainty that may be achieved using remote sensing in comparison to discrete sampling and traditional enumeration and identification. Black dots and connecting lines indicate "real" values as the HAB changes with time (e.g., may increase or decrease intensity over time). Cell density and chlorophyll-*a* in this theoretical example are correlated; however, this may not always be the case. Gray area represents a theoretical cone of uncertainty (e.g., increasing uncertainty with time) and can impact planning of a management action and efficacy measurements. Panel A, photo credit: U.S. Army Corps of Engineers Kansas City District, 2021. Panel B, image credit: U.S. Army Corps of Engineers HAB Explorer web application example for Milford Lake, Kansas, 2024; https://jecop-public.usace.army.mil/hab/.

2008; Beaton et al. 2020), it can be challenging to plan and implement management and evaluate efficacy at scale due to spatial and temporal changes in HABs (especially planktonic species) in terms of bloom density and location. Often water resource managers and decision makers have limited spatial and temporal data (e.g., grab samples) to inform when and where to manage. Further, these challenges impact the evaluation of a management action, in which field samples lack sufficient spatial and temporal coverage to thoroughly evaluate and understand efficacy. Limited spatial and temporal data often leads to uncertainty, thereby negatively impacting successful outcomes of a management plan (Figure 1) (Michalsen et al. 2024).

Given the dynamic changes possible with HABs, time is a primary factor that increases the uncertainty of HAB measurements (Figure 1). For example, traditional HAB sampling techniques often involve collection of discrete samples with limited spatial and temporal scale. These samples are then shipped to a laboratory where they are analyzed; a report is developed, and decisions are made based on that report before teams are mobilized to implement a management action (Bishop and Rodgers 2011; Isaacs et al. 2013; Geer et al. 2017; Kinley-Baird et al. 2023). During this time (days to weeks), multiple processes impact both the density and position of HAB-forming phytoplankton in a waterbody leading to potentially inaccurate assumptions regarding the HAB and, ultimately, jeopardizing management success.

Cell density is a crucial factor impacting effective management actions, particularly regarding algaecides for which exposure-response relationships are dose dependent (i.e., greater cell densities require greater algaecide treatment rates) (Kinley et al. 2017; Calomeni et al. 2018). However, monitoring cell density over space and time can be challenging for many algal species, as the growth rate and distribution within the water column are subject to several biotic and abiotic factors. For example, the density and position of a HAB can change rapidly (e.g., within an hour)

(Graham et al. 2008; Deng et al. 2016), concentrate at specific depths, move vertically as a layer within the water column, or distribute relatively evenly throughout the water column (Graham et al. 2008). Factors that impact vertical movement include the buoyancy of the phytoplankton (Verspagen et al. 2004; Misson and Latour 2011) and physical processes within the system (e.g., thermal stratification, water and wind velocities) (Graham et al. 2008; Deng et al. 2016). Factors that can influence the location of HABs horizontally include water and wind velocities as well as light, temperature, and nutrient availability (Graham et al. 2008; Deng et al. 2016). Ultimately, changes in movement, density, and composition of a HAB are likely between sample collection and management action, thereby increasing uncertainty and the risk of implementing a misinformed management action (Calomeni et al. 2017). Therefore, remote sensing and field-based sensors may provide an opportunity to decrease uncertainty and provide additional data resolution between manual sample analysis and management action, potentially saving time and resources, and reducing human or ecological risks from ineffective management.

There is an immediate need to pair additional lines of evidence from remote sensing and field-based sensor technologies with traditional methods to better inform HAB adaptive management strategies. Communication with experts in the field is critical to understand practical uses of remotely sensed data and how this technology can be realistically integrated into existing workflows (Topp et al. 2020). Although this study was exploratory in that it aims to highlight key insights and identify areas where further investigation is warranted, other recent in-depth reviews are available that explore sensing methodologies used for HABs (e.g., algorithms and machine learning approaches), hyperspectral processes (e.g., spectral bands), and novel sensor technologies (e.g., Arias et al. 2025; Kumar et al. 2025; Wang and Qin 2025). Therefore, the objectives of this study were to 1) conduct a literature review to identify existing examples of remote sensing and field-based sensors used for HAB management and 2) facilitate a meeting with experts in HAB management to identify data needs for management action as well as information gaps in using remote and field-based sensor technologies. In this paper, the data needs and information gaps identified during the meeting were expanded with support from peer-reviewed literature.

METHODS

Literature review of existing HAB management decisions informed by remote sensing and field-based sensors

This literature review was performed by searching multiple databases including Science Direct, Web of Science, IEEE Xplore Digital Library, JSTOR, Wiley Online Library, and Google Scholar. No date restrictions were applied. The purpose of this search was to identify scholarly articles focused on the use of remote sensing and field-based sensors to inform a particular HAB management action. Other authors often use the term "management" nonspecifically (i.e., the management action is not defined) or include avoidance of risk within the definition. For example, management as defined by others may include placing signage around a HAB-impacted waterbody to warn users of risks. Therefore, keyword combinations for searches were selected with the goal of identifying manuscripts that detailed a specific management action.

Each database was searched using 15 different keyword combinations. The search contained the same two keywords ("remote sensing" and "harmful algal blooms") with a third distinct keyword specific to a management action. The 15 different keywords searched were "management," "algaecide," "harvester," "dye," "flocculation," "chemical control," "remediation," "artificial mixing," "artificial circulation," "straw," "control," "decisions," "treatment," "mitigation," and "removal." Results were compiled using the management software RefWorks (ProQuest, Ann Arbor, MI) to give a list with title, author, type of article, publication date, abstract, and database. Manuscript titles and abstracts were reviewed to identify those that pertained specifically to remote and field-based sensors used for management. Criteria for inclusion were peer-reviewed journal articles written in English that were within scope.

Expert meeting

Input from experts was solicited during the 64th meeting of the Aquatic Plant Management Society (APMS) held in St. Petersburg, FL, at a meeting on 17 July 2024 at 1:10 P.M. The expert meeting held at APMS was open to all attendees. APMS was selected as the venue to hold this expert meeting because attendees consist of professionals from different sectors and industries, many of which have conducted or guided HAB management, while some have expertise in remote and field-based sensors. This ensured that feedback was grounded in practical expertise and reflected scientific and management perspectives relevant to the scope of this study.

The meeting was attended by 32 professionals representing industry (44%), academia (31%), government (16%), and nonprofit or public organizations (9%). Seven individuals had previously presented a topic related to remote sensing, mostly remote sensing for nuisance and invasive aquatic plant management, at APMS within the last 5 yr. Industry represented individuals that plan HAB management activities consisting of chemical, mechanical, physical, biological, and nutrient management sectors as well as algaecide manufacturers and a remote sensing company (Figure 2).

After an introduction to the context of the study, experts were verbally asked guiding questions, and free form conversation followed each question in series. A member of the research team served as a dedicated note taker during discussion. Questions were as follows:

1) What data are important in making a HAB management decision?
2) What remote sensing and field-based sensor technologies are currently being used by industry?
3) What technologies are the most promising, and which ones are not working?
4) What are issues associated with analyzing or managing data to reach a HAB management decision?

Meeting notes were maintained during discussion and were informally analyzed. The group was asked to review an earlier draft of this manuscript with individuals providing

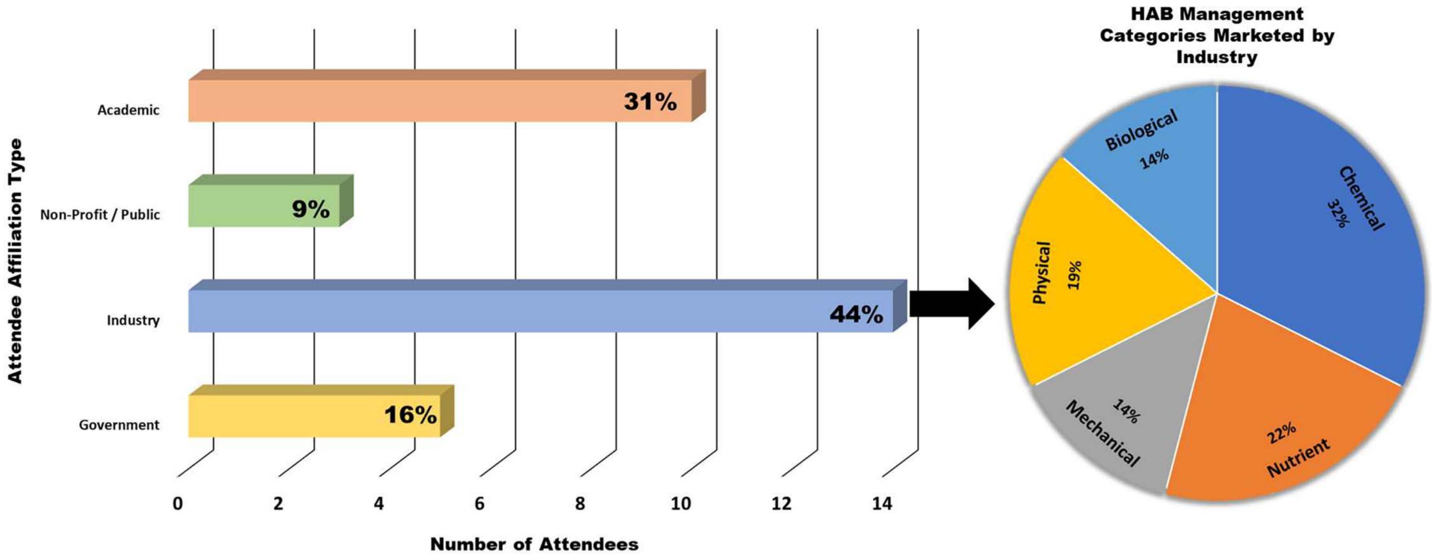

Figure 2. Composition of experts that attended a remote and field-based sensor meeting for harmful algal bloom management during the 64th meeting of the Aquatic Plant Management Society (APMS) held in St. Petersburg, FL, in 2024.

support of text in this document included as coauthors as appropriate.

RESULTS AND DISCUSSION

Literature review of existing HAB management decisions informed by remote and field-based sensors

We identified 199 manuscripts spanning 1997–2024 with 24 manuscripts listing management as a keyword (Figure 3); however, only five of 199 papers (2.5%) specifically referenced using remotely sensed data or data obtained from field-based sensors in the context of a management decision (Table 3). These results highlight the need for additional sensor research grounded in HAB management decision

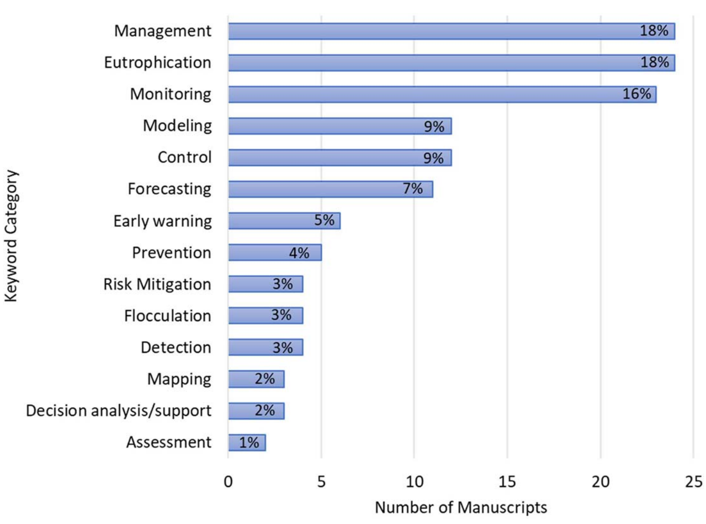

Figure 3. Number and percent of manuscripts grouped by keyword categories that were identified in the literature review. Keywords were grouped into categories based on synonymous terms. Keywords that were not action focused (e.g., harmful algal bloom, cyanobacteria) are not included as well as keywords listed in only a single manuscript.

making and emphasizes the importance of incorporating expert input, as done at an exploratory level in this paper. Two papers used data obtained from remote or field-based sensors to measure parameters necessary in determining if a management trigger had been reached in the context of drinking water resources (Adams et al. 2022; Alayande et al. 2022). HABs often occur intermittently or seasonally in many locations, therefore consistently managing a drinking water facility as though a HAB is mostly present would be an inefficient use of chemicals. Therefore, drinking water facilities establish triggers indicating that a change in management action needs to be performed. For the city of Wichita Falls, TX, *in situ* multiparameter sondes with wipers were deployed strategically outside and within the drinking water treatment facility. Increases in pigment concentrations were used to indicate that more frequent source water monitoring was needed as well as the location and timing of sample collection. Once a HAB was confirmed via traditional laboratory analyses, the utility company may switch source water intakes to a lake without a bloom, implement in-lake treatments, or alter chemical addition within the plant (Adams et al. 2022). Another example is desalinization facilities that provide a critical source of potable water and are sensitive to HABs that can clog filtration systems. Alayande et al. (2022) discussed a theoretical example of using satellite remote imagery and drones to track HAB events and provide an early warning to optimize desalinization processes.

Another study suggested using remotely sensed data to characterize HAB severity among waterbodies. Some industrial sectors (e.g., energy companies) as well as state and federal agencies are responsible for the management of multiple lakes. Mishra et al. (2019) presented methods for calculating area-normalized HAB magnitude using remotely sensed imagery that could be used to rank waterbodies in terms of HAB severity. Ranking could then be used to prioritize waterbodies requiring the most attention and resources for management. In a different study, satellite imagery from the Sentinel-3 Ocean and Land Colour Instrument (OLCI) was compared to data collected from *in situ* sampling of the Lake Okeechobee waterway (Reynolds et al. 2023). Remote sensing provided data with higher spatial and temporal frequency that could be used to track HAB location relative to downstream discharge points without significant labor and cost increases often associated with *in situ* sampling. The authors provide an example of the use of remote sensing data to inform the timing of reservoir releases if a HAB is present at a discharge point to reduce or mitigate downstream impacts. Lastly, monitoring of management effectiveness using field-based sensors was highlighted in Calomeni-Eck et al. (2024), in which a pilot algaecide treatment was performed within a pond that was divided into treated and untreated areas. Two *in situ* multiparameter sondes, one each in the treated and untreated areas, were used to monitor chlorophyll-*a* and phycocyanin concentrations after management. The sondes provided pigment data at high temporal resolution and were used as a line of evidence in addition to traditional sampling and analysis methods to interpret treatment effectiveness.

In Adams et al. (2022) and Calomeni-Eck et al. (2024), field-based sensor technologies were used in conjunction with traditional sampling and analysis techniques. This is a rational approach for the novel use of these technologies for management decision making. For example, drinking water facilities represent a high-risk scenario where misinformed decisions could lead to adverse outcomes. The use of field-based sensors to fill data gaps informing when and where to sample utilizes the benefits provided by high temporal resolution data (Adams et al. 2022). Ultimately, the lack of manuscripts focused on the use of remote sensing and field-based sensors to inform management highlights opportunities in this area of research.

Expert meeting

A meeting with a group of experts was convened to discuss and identify key data gaps for how sensors could be used to inform management actions related to HABs. The experts emphasized the need for improved real-time monitoring capabilities to detect HABs early and accurately. They also highlighted gaps in the integration of remote sensing and field-based sensor data with traditional sampling, noting the challenges in harmonizing datasets and uncertainties from different platforms. Insights from the meeting were grouped into key areas of interest that were developed further in the seven sections outlined below:

1. Establish necessary data for management and when data are used for decision making
2. Use of remote sensing and field-based sensors to identify HAB taxa
3. Determination of HAB cell density and chlorophyll-*a* concentration
4. Determination of toxin concentrations
5. Determination of HAB spatial distribution in the water column
6. Remote sensing and field-based sensor data integration with traditional methods
7. Understanding key limitations or challenges with remote sensing and field-based sensor data.

Expert input—Necessary data and timing for decision making

Data are needed to make multiple management decisions at different times during the management process, including the following: 1) identifying when management is necessary, 2) informing an appropriate management action and where it should be implemented, and 3) evaluating management efficacy (Huddleston et al. 2015; Calomeni et al. 2017; Geer et al. 2017; Kinley-Baird et al. 2023; Calomeni-Eck et al. 2024). To identify when management is necessary, action thresholds are established that refer to a specific quantity of a parameter before HAB impairment is unacceptable (Calomeni et al. 2017). Thresholds for HABs can be cell density, toxin concentration, or concentrations of specific taste and odor compounds that create unpalatable drinking water (e.g., geosmin and 2-methylisoborneol). For example, at a drinking water facility, a risk-based action threshold could be below the USEPA drinking water health advisory level for microcystins and/or below the human detection limit for taste and odor compounds. In industrial settings where the management goal is to remain within NPDES permit requirements, thresholds are often pH and/or total suspended solids in discharge waters.

To inform an appropriate management action, the phytoplankton taxa, relative abundance of each taxon, and total cell density of the assemblage are necessary data as well as the location and extent of the phytoplankton horizontally over the water surface and vertically in the water column. Additional water characteristics, primarily dissolved oxygen levels and water temperature (both spatially and vertically), are also needed to determine whether a management action that could rapidly kill cyanobacteria or algae cells would be safe for nontarget organisms due to biological oxygen demand.

Lastly, to determine management efficacy, the target parameter of interest (e.g., cell density, toxin concentration, or taste and odor concentration) following management can be compared to the value for that parameter prior to management and to the action threshold itself. For algaecide applications administered to waters of the United States, as a management action, cyanobacterial or algal taxa, cell density, surface area, location, and toxin concentrations may be required by state and federal law to meet permitting requirements (Calomeni et al. 2017).

Further, in locations where a strategic decision has been made toward the long-term management of HABs, descriptive data are needed for adaptive management (Netherland and Schardt 2021) (Figure 4). Adaptive management is a process that is often appropriate for HAB impacted locations as it facilitates decision making in situations where unknowns are expected, such as changing conditions as management progresses and fluctuating environmental conditions. Identification of an action threshold is captured by "HAB problem formulation" and "plan and prioritize" phases of the adaptive management process (Figure 4).

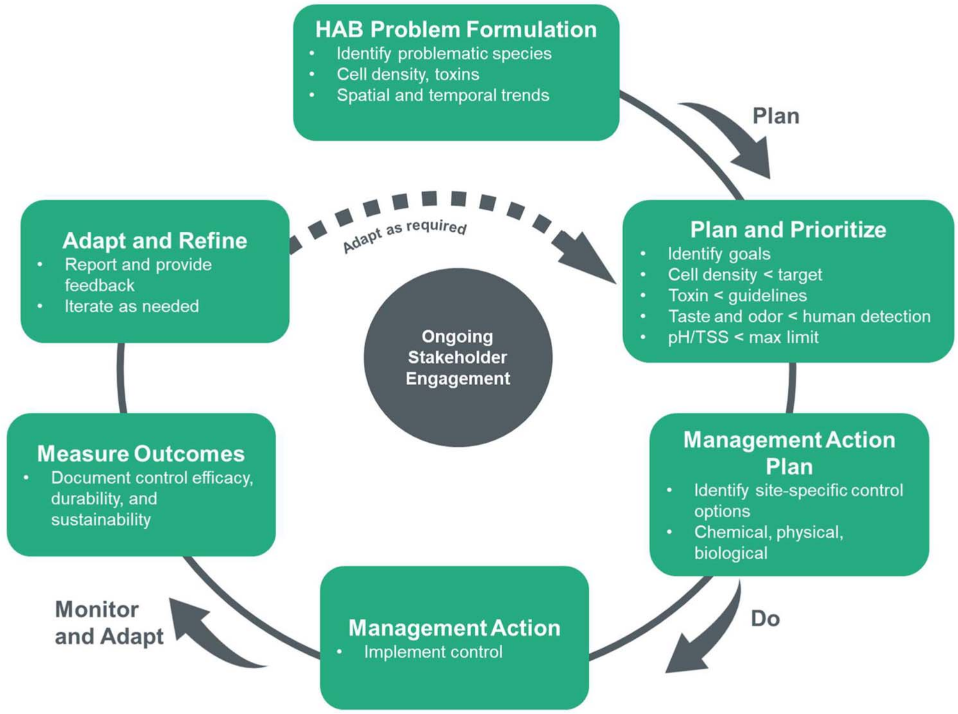

Figure 4. Harmful Algal Bloom (HAB) Adaptive Management Plan (adapted from NRC 2004, Williams et al. 2009, CMP 2013, McQueen et al. 2024).

These phases are critical to develop a scientific basis for the management action and identified goals. Characterizing the cyanobacterial or algal taxa, cell density, and HAB location is needed to identify site-specific control options within the "management action plan" phase. Comparison of pre- and postmanagement conditions is needed to discern how effective the management action was during the "measure outcomes" phase so that management actions can be refined as part of the "adapt and refine" phase. Ultimately, parameters such as cell densities and toxin concentrations need to be determined in multiple management phases and remote sensing and field-based sensor technologies that can be used to either quantify these specific parameters or inform sample collection (i.e., when and where) are useful for management decision making (Table 1).

Identification of HAB taxa

Phytoplankton can consist of harmful or problematic taxa that are the focus of management as well as beneficial (e.g., food source for higher trophic levels) or benign taxa that are not the intended target of management; therefore, identification of specific target taxa is often critical for management success and to characterize potential risks and issues caused by the HAB. Researchers are investigating the potential to use spaceborne, airborne, surface-based, and submersed sensors coupled with machine learning methods

Table 1. List of data to support the management of HABs.

1. Necessary data[1]
Total impacted acreage targeted for management
Map of area to be managed
HAB location horizontal over water surface, vertical within water column, and surface area extent
Algal taxa identification and assemblage composition
Cell density, biovolume, biomass
Algal toxin concentrations: measurement of algal toxins (e.g., microcystins, cylindrospermopsins, anatoxin-a, and saxitoxins)
2. Biological, chemical, physical data (spatial and temporal)
Algal pigments: chlorophyll-*a*, phycocyanin aggregate data to estimate relative amount of algae
Algal secondary byproducts: taste and odor (geosmin, 2-methylisoborneol [MIB])
Water quality data: temperature, pH, dissolved oxygen, nutrient concentrations, light attenuation, turbidity, total suspended solids, conductivity, alkalinity
Hydrological data: Mapping currents and water flow that influence bloom location and contact time (e.g., algaecide)
3. Historical and predictive modeling data
Historical bloom data:helps in predicting and understanding the timing and frequency of HABs
Long-term climate data: temperatures and changes in precipitation patterns, extreme weather events
Forecast models: use of predictive models incorporating meteorological, hydrological, biological to forecast bloom occurrences

[1]Data requirements are specific to the management technique and the state. These data may be required by state and federal agencies for algaecide permits.

to distinguish HAB taxa. Identification of HAB taxa is primarily based on imagery (e.g., flow imaging microscopy, multispectral or hyperspectral reflectance in visible and near-infrared spectrum), which may highlight the presence or absence of specific algal taxa, such as cyanobacteria via the pigment phycocyanin (Randolph et al. 2008; Pokrzywinski et al. 2021; Slonecker et al. 2021; Legleiter et al. 2022; Rolim et al. 2023; Fournier et al. 2024). The utility of these optical methods varies widely, especially because of the variability in sensor capabilities. For example, the spatial resolution of imagery ranges from micrometers with submersible microscopes to hundreds of meters per pixel with satellites. At microscopic scales, individual cells may be identified and enumerated, whereas at centimeter- and meter-level scales, the aggregate absorption and backscattering properties of the water column can indicate the presence or absence and relative abundance of cyanobacteria based on the unique spectral profile of different phytoplankton taxa. Such spectral profiles can be examined in laboratory environments where field-collected and pure HAB cultures are grown under a variety of conditions (e.g., low to high light and nutrient concentrations) that may impact the spectral signatures of taxa, and then imaged using a hyperspectral sensor (Pokrzywinski et al. 2021). Specifically, the laboratory methods described in Pokrzywinski et al. (2021) were used to evaluate deviations between spectral signatures of different cyanobacteria, suggesting that hyperspectral-based methods hold promise for identifying taxa. This approach requires validation in the field as there are distinct visual changes that occur to cyanobacteria in culture as in the case of *Microcystis aeruginosa* that often is present as single cells but aggregated in colonies in the field (Zhang et al. 2007; Salmaso et al. 2014). Additionally, in the field, cyanobacteria may exist in the presence of suspended sediment and as an algal assemblage that may impact spectra (Legleiter et al. 2022).

Determination of HAB cell density and chlorophyll-a concentration

Satellite imagers (e.g., PlanetScope, Worldview-2, Sentinel-2) can be used to assess water conditions by measuring reflected light from the water surface at specific wavelengths. Common wavelengths used for detection of HABs are green reflectance (near 550 nm), chlorophyll-*a* absorption (665 nm –680 nm), chlorophyll-*a* fluorescence (683 nm), and cell backscattering (705 to 709 nm) (Davis et al. 2007; Kutser 2009; Shen et al. 2012; Stumpf et al. 2016b; Lekki et al. 2019). Over the past few decades, there has been an increase in research for the development of spectrally based algorithms which utilize these spectral features to generate indices applied to imagery to quantify chlorophyll-*a* concentrations or provide relative estimations that can be used for estimating HAB density (Glazer et al. 1973; Gregor and Marsalek 2004; Dall'Olmo and Gitelson 2005; Kutser 2009; Lunetta et al. 2015; Beck et al. 2016). While a full review of remote-sensing–derived HAB algorithms is beyond the scope of this paper, some notable examples are the Normalized Difference Chlorophyll Index (NDCI), Chlorophyll/Cyanobacterial Index (CI), and Maximum Chlorophyll Index (MCI) (Wynne et al. 2008; Mishra and Mishra 2012; Binding et al. 2013; Seegers et al. 2018). Resulting map products illustrate the extent of chlorophyll-*a* or potential HAB conditions across the surface of a waterbody, providing a wholistic view and broad spatial context to managers.

Determination of toxin concentrations

Direct detection of toxins is not currently possible using satellite and airborne imaging technologies. However, researchers have developed methods to investigate relationships among photosynthetic pigment concentrations discerned via satellite imagery and toxin concentrations (e.g., 0.1 to 40 $\mu g\ L^{-1}$ as individual microcystin congeners) traditionally analyzed in the laboratory using ELISA (Douglas 2020; Douglas Greene et al. 2021). Stronger correlations occur when predictions are made within a waterbody or within waterbodies with similar characteristics (Douglas 2020) relative to large spatial scales (e.g., the state of Iowa). Similarly, correlations are anticipated to decrease with longer temporal durations. This is due to photosynthetic pigment concentrations being aggregate measurements of algae and not direct measurements of toxin concentrations. Photosynthetic pigments are contained by multiple algae and cyanobacteria including nontoxin and toxin-producing taxa. Within a waterbody, the same toxin producer may be more likely to reoccur resulting in greater correlations at this smaller temporal and spatial scale. However, toxin production by cyanobacteria is often intermittent and could be correlated with a range of internal and external factors, and as such, toxin analysis is necessary to confirm toxin concentrations.

A few autonomous toxin sampling and analytical devices have been explored (Herranz et al. 2012; Maguire et al. 2018; Ussler et al. 2024) (Environmental Sample Processor, McLane Laboratories, East Falmouth, MA). These devices could be placed on a buoy or autonomous vehicle for independent sample collection and toxin measurement. For example, Ussler et al. (2024) described an autonomous sampling system whereby three separate autonomous innovations, including the vehicle, sampler, and analytical instrument, were deployed and evaluated in western Lake Erie. The system is an autonomous underwater vehicle capable of deployments lasting 10 to 14 days. The environmental sampler conducts sampling, filtration, cell lysis, and preservation depending on the analytical needs. The small-scale (e.g., penny-sized) on-board analytical instrument uses surface plasmon resonance for microcystin measurement. These technologies are emerging as turnkey autonomous devices using USEPA-approved methods for toxin detection but are not currently available commercially.

Determining HAB distribution—Horizontally over water surface

Satellite imagery is a fit-for-purpose technology used to estimate HAB coverage over the water surface. Imagery can be used to estimate HABs with moderate to high cyanobacterial cell densities defined by the World Health Organization as above 100,000 cell/ml and for waterbodies ranging in size from a small waterbodies ($< 0.01\ km^2$) (Mullen et al. 2023) to a large lake (e.g., the Great Lakes) depending on the sensor (Clark et al. 2017; Coffer et al. 2021). Common satellite remote sensing research focuses on HAB monitoring using a variety of algorithms or band ratios for establishing HAB location and surface area extent (Wynne et al.

Table 2. Examples of nationally focused satellite remote sensing tools, platforms, and web applications.

Web-based tools, platforms, and applications	URL	Citation
Sentinel Hub's EO Browser[1]	https://apps.sentinel-hub.com/eo-browser/	(EO Browser 2024; Sentinel Hub 2024)
EPA's Cyanobacteria Assessment Network v1.1.52	https://qed.epa.gov/cyanweb/account	(Schaeffer et al. 2015)
USACE's *waterquality* R tool v1.0	https://github.com/RAJohansen/waterquality	(Johansen et al. 2019)
USACE's *waterquality* for ArcGIS Pro toolbox v1.1	https://erdc-library.erdc.dren.mil/jspui/handle/11681/42240	(Saltus et al. 2022)
USACE's HAB Explorer	https://jecop-public.usace.army.mil/hab/	Not applicable
bloomWatchv5	https://cyanos.org/bloomwatch/	Not applicable

[1]EO Browser does not have a specific HAB product, but users can customize band ratio algorithms for HABs (e.g., normalized difference chlorophyll index).

2008; Mishra and Mishra 2012; Binding et al. 2013; Beck et al. 2016; Seegers et al. 2018). Spectrally based algorithms have accurately estimated HAB indicators, such as chlorophyll-a (Seegers et al., 2018), assess regional and national HAB conditions (Clark et al. 2017; Coffer et al. 2021), and quantify monthly bloom changes, including to help inform management decisions (e.g., strong correlations between *in situ* and remote sensing-based estimations with a Kendall's tau value of 0.85) (Reynolds et al. 2023). Thus, a variety of web-based platforms or tools utilizing satellite imagery currently exist for detecting and mapping HABs (Table 2). As most studies focus on HAB monitoring, a more thorough understanding of remote sensing accuracies for management decision making is a topic that would require additional research. Although satellite imagers typically measure signal return from the water surface or near-surface (e.g., approximately the top meter of the water column depending on water conditions), additional sensors are needed to discern conditions below the water surface.

Determining HAB distribution—Vertically in water column

The usefulness of *in situ* sondes for detection of HABs using HAB indicators (e.g., chlorophyll-*a* and phycocyanin concentrations, pH, and dissolved oxygen) has been previously demonstrated and reported in this paper. However, deploying *in situ* sondes at discrete depths within a water column could be used to track the vertical location of HABs. There are multiple commercial companies that advertise near real-time data logging capabilities associated with *in situ* sondes that transmit data to a cloud data repository for access via cellular device and web browser. This can provide rapid assessment of HAB depth, but the HAB would need to be located at the sensor for detection.

An emerging area of research is the use of remote sensing reflectance to measure the vertical distribution of HABs. Kwon et al. (2020) measured *in situ* remote sensing reflectance at three discrete depths (below surface, 50 cm, and 100 cm) using a portable sensor combined with a UAS-mounted hyperspectral sensor (Kwon et al. 2020), whereas Moore et al. (2019) applied airborne LiDAR to evaluate algal concentration and to discriminate between two cyanobacteria genera (*Microcystis* and *Planktothrix*) by their differing vertical position in the water column (*Microcystis* was consistently closer to the water surface) (Moore et al. 2019). Although the application of many of the mentioned technologies is still in its infancy, they demonstrate the benefits of integrating various remote sensing approaches for improved management decision making as these tools and techniques become more available.

Remote sensing data integration with traditional methods

Integrating satellite remote sensing data with traditional sampling methods (e.g., grab sampling) for the management of HABs offers numerous benefits to enhance efficiency, monitoring, and response strategies. First, multiplatform/sensor data integration allows for comprehensive spatial coverage. While remote sensing provides broad-scale, near real-time observations of waterbodies (Gons et al. 2008;

Table 3. Summary of manuscripts that discussed remote and field-based sensors for management decision making.

Location	Water body	Purpose	Remote or field-based sensor	Citation
Wichita Falls, TX	Source water of drinking water facility	Increases in pigments suggest more frequent monitoring to determine if source water intakes need to be switched, in-lake treatments or chemical additions within plant needed	Field-based (multiparameter sonde)	Adams et al. (2022)
Mediterranean Sea, Arabian Gulf, Gulf of Oman and Red Sea	Source water of desalinization facility	Hypothetical situation: Early warning to optimize desalinization process	Remote (satellite and drone imagery)	Alayande et al. (2022)
Big Eleven Lake, Kansas City, KS	Pond	Line of evidence in addition to traditional sampling to interpret algaecide treatment effectiveness	Field-based (multiparameter sonde)	Calomeni-Eck et al. (2024)
Florida and Ohio	Multiple water bodies	Rank water bodies for management based on HAB severity	Remote (satellite imagery–ENVISAT and MERIS)	Mishra et al. (2019)
Lake Okeechobee Waterway, FL	Lake	Inform timing of reservoir releases if a HAB is present at discharge point to reduce downstream impacts	Remote (satellite imagery–Sentinel-3 Ocean and Land Colour Instrument [OLCI])	Reynolds et al. (2023)

Moses et al. 2009; Wang et al. 2020; Johansen et al. 2024), traditional grab sampling offers high-fidelity data at specific locations, enabling more precise assessments of algal composition and comparisons of estimated algal pigment data (e.g., satellite derived chlorophyll-*a*) with cell density (cell/ml). This synergy helps to validate and calibrate remote sensing algorithms, improving the accuracy of biomass estimates and enabling better characterization of bloom dynamics (Ma et al. 2021; Zhou et al. 2023). Additionally, remote sensing data can be used to inform the timing and location of grab sampling efforts, making field sampling more efficient and focused on areas of high algal concentration. By combining the strengths of both approaches, resource managers can develop more effective predictive models for bloom occurrence and intensity, leading to timely interventions (Stumpf et al. 2016a; Hill et al. 2020; Gupta et al. 2023; Schaeffer et al. 2024). Furthermore, this integration enhances data richness, facilitating a more comprehensive understanding of the factors driving HABs, and ultimately leading to improved decision making for water quality management and public health protection.

Challenges of remote sensing data for application to HAB management

Data analysis and management using satellites and remote sensing for managing HABs presents several challenges. First, the data volume generated by remote sensing, particularly imagery with high spatial and temporal resolutions, requires robust cyber-storage and processing capabilities. Data integration from multiple sources, such as different satellite platforms or combining remote sensing with *in situ* data, can be complex due to varying spatial resolutions, spectral bands, and temporal frequencies (Glibert et al. 2018; Khan et al. 2021). Satellite imagery can be affected by environmental factors like cloud cover, atmospheric interference, and water turbidity, leading to potential false positives or missed HAB detection (Dall'Olmo and Gitelson 2005; Li et al. 2010; Park et al. 2010; Matthews 2017; Xu et al. 2019). Computational limitations can arise, especially in real-time processing, which is necessary for timely management responses. Moreover, costs associated with accessing high-resolution or proprietary data and technical expertise required to process and interpret the data can be barriers to resource managers wanting to adopt these technologies for management purposes. Finally, creating actionable insights from these data involves developing advanced models capable of predictive analysis while balancing the need for accuracy with the complexity of big data.

However, there are opportunities to decrease the "barrier to entry" for using remote sensing and field-based sensor technologies for actionable HAB management decisions. For example, advancements in cloud computing and storage have led to a dramatic improvement in the development of user-focused software and web-based applications (Woodcock et al. 2020; Khan et al. 2021). Notably, open-source programming and web apps have helped reduce technical barriers and enabled the integration of remotely sensed imagery as a complementary tool for monitoring HABs to aid decision making and management goals (Schaeffer et al. 2015; Johansen et al. 2019; Saltus et al. 2022; EO Browser 2024; Sentinel Hub 2024) (Table 2).

SUMMARY AND PATH FORWARD

HAB management has become increasingly complex given the diversity of nuisance algal species and apparent stochastic nature of HAB distribution over space and time. Resource managers often have limited spatial and temporal data to inform when and where to treat HAB occurrences. There are emerging remote sensing and field-based sensor data, tools, and applications that potentially offer substantial value for improved data collection to inform HAB management decisions. Five studies were identified that used remote or field-based sensors to 1) prioritize areas potentially requiring management, 2) provide an early warning or trigger a change in management action, and 3) provide more robust lines of evidence for management efficacy. Additionally, emerging technologies may be useful to aid in the identification of HAB taxa and horizontal and vertical distribution in the water body. The currently limited number of published studies reporting the intentional integration of remote sensing and field-based sensor technologies with HAB management highlight the need to better understand their value and to explore future real-world applications. Therefore, a meeting with experts in the field of HAB management was facilitated to understand data needs and opportunities to integrate remote sensing and field-based sensor technologies into adaptive management processes and decision making to mitigate the adverse impacts of HABs. Key perspectives, data gaps, and future research needs during this meeting included the following:

- Often, management decisions are based on data simplified to a few averaged values reflecting the target nuisance algal species and algal cell density or biomass.
- There is much interest in new remote sensing and field-based sensor technologies that can offset time and resource demands for HAB field monitoring programs.
- Traditional monitoring approaches (e.g., grab sampling, etc.) will need to be strategically used to integrate or optimize remote sensing and field-based sensors to provide improved near-real time information.
- There are benefits for aggregation of historical information to inform predictive tools or modeling of future HAB events.
- More awareness is needed of real-world field case study examples using emerging tools for management decisions.
- Approaches and tools are needed for managing and analyzing large datasets (such as those gathered during remote sensing) into single actionable values.
- Real-time sensing of algae during treatment could improve efficiency (e.g., sensors informing application rates in real time).
- Uncertainty needs to be captured and communicated for sensor data (selectivity, sensitivity, reproducibility).
- Better understanding of appropriate statistical tools or methods that can be applied to large, skewed data or data with a small number of replicates (e.g., pseudo-replication).

ACKNOWLEDGEMENTS

This research was funded by the United States Army Corps of Engineers (USACE) Aquatic Nuisance Species Research Program (ANSRP). The authors declare no conflict of interest.

LITERATURE CITED

Adams H, Smith SA, Reeder S, Appleton E, Leinweber B, Forbes S, Barrowman P, Ford G, Ikehata K, Southard M. 2022. Characterizing and mitigating cyanobacterial blooms in drinking water reservoirs. Am. Water Works Assoc. 114:26–38.

Alayande AB, Lim J, Kim J, Hong S, Al-Amoudi AS, Park B. 2022. Fouling control in SWRO desalination during harmful algal blooms: A historical review and future developments. Desalination 543:116094.

Arias F, Zambrano M, Galagarza E, Broce K. 2025. Mapping harmful algae blooms: The potential for hyperspectral imaging technologies. Remote Sens. 17:608.

Beaton ML, Binding C, Bontje J, Bullerjahn GS, Creed IF, Crossman J, DeRoy EM, Dominato KR, Drouillard K, Eimers MC, Frenken T, Friedman KB, Grgicak-Mannion A, Helm PA, Hummel SL, King CK, Kohno S, Korn VR, Lafontaine J, Liu F, MacIsaac HJ, Mashhadi N, McKay RML, McKindles K, McPhedran K, Mundle SOC, Sayers MJ, Schoenfuss HL, Shuchman RA, Stumpf RP, Szalinska E, Wang LC, Weidman RP, Weisener C. 2020. Contaminants of the Great Lakes. Hutzinger O, editor. Windsor, Canada: Springer.

Beck R, Zhan S, Liu H, Tong S, Yang B, Xu M, Ye Z, Huang Y, Shu S, Wu Q, Wang S. 2016. Comparison of satellite reflectance algorithms for estimating chlorophyll-*a* in a temperate reservoir using coincident hyperspectral aircraft imagery and dense coincident surface observations. Remote Sens. Environ. 178:15–30.

Binding C, Strumpf R, Shuchman RA, Sayers M. 2020. Advances in remote sensing of Great Lakes algal blooms, pp. 217–232. In: J. Crossman and C. Weisener (eds.). Contaminants of the Great Lakes. Springer Nature, Cham, Switzerland.

Binding CE, Greenberg TA, Bukata RP. 2013. The meris maximum chlorophyll index; its merits and limitations for inland water algal bloom monitoring. J. Great Lakes Res. 39:100–107.

Bishop WM, Rodgers JH. 2011. Responses of *Lyngbya magnifica* Gardner to an algaecide exposure in the laboratory and field. Ecotoxicol. Environ. Saf. 74:1832–1838.

Brooks BW, Lazorchak JM, Howard MD, Johnson MV, Morton SL, Perkins DA, Reavie ED, Scott GI, Smith SA, Steevens JA. 2016. Are harmful algal blooms becoming the greatest inland water quality threat to public health and aquatic ecosystems? Environ. Toxicol. Chem. 35:6–13.

Calomeni A, Kinley CM, Geer TD, Hendrikse M, Rodgers J. 2018. *Lyngbya wollei* responses to copper algaecide exposures predicted using a concentration– exposure time (CET) model: Influence of initial biomass. J. Aquat. Plant Manage. 56:73–83.

Calomeni AJ, Geer TD, Iwinksi KJ, Rodgers JH, Madsen JD, Wersal RM. 2017. Monitoring for national pollutant discharge elimination system permit requirements: Algaecides. J. Integrated Pest Manage. 8:1–9.

Calomeni-Eck A, McQueen A, Kinley-Baird C, Smith E, Growcock B, Decker K, Hampton S, Stahl A, Boyer M, Clyde G. 2024. Demonstration of proactive algaecide treatments targeting overwintering cyanobacteria in sediments of an urban pond. Water 16:1624.

Campbell J, Wynne R. 2011. History and scope of remote sensing. Introduction to remote sensing. 5th ed. Guilford Publications, New York.

[CDC] Centers for Disease Control and Prevention. 2021. Summary report—One health harmful algal blooms system (OHHABS). Centers for Disease Control and Prevention, Atlanta.

Christensen VG, Crawford CJ, Dusek RJ, Focazio MJ, Fogarty LR, Graham JL, Journey CA, Lee ME, Larson JH, Stackpoole SM, Mazzei V. 2024. Interdisciplinary science approach for harmful algal blooms (HABS) and algal toxins—A strategic science vision for the U.S. Geological Survey. U.S. Geological Survey Circular No. 1520.

Clark JM, Schaeffer BA, Darling JA, Urquhart EA, Johnston JM, Ignatius A, Myer MH, Loftin KA, Werdell PJ, Stumpf RP. 2017. Satellite monitoring of cyanobacterial harmful algal bloom frequency in recreational waters and drinking source waters. Ecol. Indic. 80:84–95.

[CMP] Conservation Measures Partnership. 2013. Open standards for the practice of conservation. Conservation Measures Partnership.

Coffer MM, Schaeffer BA, Salls WB, Urquhart E, Loftin KA, Stumpf RP, Werdell PJ, Darling JA. 2021. Satellite remote sensing to assess cyanobacterial bloom frequency across the United States at multiple spatial scales. Ecol. Indic. 128:107822.

Dall'Olmo G, Gitelson A. 2005. Effect of bio-optical parameter variability on the remote estimation of chlorophyll concentration in turbid productive waters: Experimental results. Appl. Optics 44:412–422.

Davis C, Kavanaugh M, Letelier R, Bissett WP, Kohler D. 2007. Spatial and spectral resolution considerations for imaging coastal waters. Coastal Ocean Remote Sensing. Proceedings of SPIE - The International Society for Optical Engineering 6680:734288.

Deng J, Chen F, Liu X, Peng J, Hu W. 2016. Horizontal migration of algal patches associated with cyanobacterial blooms in an eutrophic shallow lake. Ecol. Eng. 87:185–193.

Douglas S. 2020. Using multispectral imagery to predict microcystin toxicity in Iowa lakes. University of Iowa.

Douglas Greene SB, LeFevre GH, Markfort CD. 2021. Improving the spatial and temporal monitoring of cyanotoxins in Iowa lakes using a multiscale and multi-modal monitoring approach. Sci. Total Environ. 760:143327.

EO Browser. 2024. https://apps.sentinel-hub.com/eo-browser/. Sinergise Solutions d.o.o., a Planet Labs company.

Fournier C, Quesada A, Cires S, Saberioon M. 2024. Discriminating bloom-forming cyanobacteria using lab-based hyperspectral imagery and machine learning: Validation with toxic species under environmental ranges. Sci. Total Environ. 932:172741.

Geer TD, Calomeni AJ, Kinley CM, Iwinski KJ, Rodgers JH. 2017. Predicting in situ responses of taste- and odor-producing algae in a southeastern US reservoir to a sodium carbonate peroxyhydrate algaecide using a laboratory exposure-response model. Water Air Soil Pollut. 228:53.

Glazer AN, Fang S, Brown DM. 1973. Spectroscopic properties of c-phycocyanin and of its α and β subunits. J. Biol. Chem. 248:5679–5685.

Glibert P, Berdalet E, Burford M, Pitcher G, Zhou M. 2018. Global ecology and oceanography of harmful algal blooms. Springer, Switzerland.

Gons HJ, Auer MT, Effler SW. 2008. Meris satellite chlorophyll mapping of oligotrophic and eutrophic waters in the Laurentian Great Lakes. Remote Sens. Environ. 112:4098–4106.

Graham JL, Loftin KA, Ziegler AC, Meyer MT. 2008. Guidelines for design and sampling for cyanobacterial toxin and taste-and-odor studies in lakes and reservoirs: USGS scientific investigations report. United States Geological Survey No. 2008-5038.

Gregor J, Marsalek B. 2004. Freshwater phytoplankton quantification by chlorophyll a: A comparative study of in vitro, in vivo and in situ methods. Water Res. 38:517–522.

Gupta A, Hantush MM, Govindaraju RS. 2023. Sub-monthly time scale forecasting of harmful algal blooms intensity in Lake Erie using remote sensing and machine learning. Sci. Total Environ. 900:165781.

Herranz S, Marazuela MD, Moreno-Bondi MC. 2012. Automated portable array biosensor for multisample microcystin analysis in freshwater samples. Biosens. Bioelectron. 33:50–55.

Hill PR, Kumar A, Temimi M, Bull DR. 2020. Habnet: Machine learning, remote sensing-based detection of harmful algal blooms. IEEE J. Select. Topics Appl. Earth Observ. Remote Sens. 13:3229–3239.

Huddleston M, Rodgers J, Wardlaw K, Geer TD, Calomeni A, Willett S, Barrington J, Melton D, Chastain J, Bowen M, Spacil M. 2015. Adaptive water resource management for taste and odor control for the Anderson regional joint water system. South Carolina American Water Works Association and Water Environment Association of South Carolina, Columbia.

Isaacs DA, Brown RG, Ratajczyk WA, Long NW, Rodgers JH, Schmidt JC. 2013. Solve taste-and-odor problems with customized treatment. Opflow 39:26–29.

Jewett EB, Lopez CB, Dortch Q, Etheridge SM, Backer LC. 2008. Harmful algal bloom management and response: Assessment and plan. Interagency Working Group on Harmful Algal Blooms, Hypoxia, and Human Health of the Joint Subcommittee on Ocean Science and Technology, Washington, DC.

Johansen R, Katzenmeyer AW, Pokrzywinski K, Reif M. 2023. A review of sensor-based approaches for monitoring rapid response treatments of cyanohabs. U.S. Army Engineer Research and Development Center. Vicksburg, MS.

Johansen R, Reif M, Emery E, Nowosad J, Beck R, Xu M, Liu H. 2019. Waterquality: An open-source R package for the detection and quantification of cyanobacterial harmful algal blooms and water quality. U.S. Army Engineer Research and Development Center. No. USACE ERDC/EL TR-19-20. Vicksburg, MS.

Johansen RA, Reif MK, Saltus CL, Pokrzywinski KL. 2024. A broadscale assessment of Sentinel-2 imagery and the Google Earth engine for the nationwide mapping of chlorophyll *a*. Sustainability 16:2090.

Khan RM, Salehi B, Mahdianpari M, Mohammadimanesh F, Mountrakis G, Quackenbush LJ. 2021. A meta-analysis on harmful algal bloom (HAB) detection and monitoring: A remote sensing perspective. Remote Sens. 13:4347.

Kinley CM, Iwinski KJ, Hendrikse M, Geer TD, Rodgers JH, Jr. 2017. Cell density dependence of microcystis aeruginosa responses to copper algaecide concentrations: Implications for microcystin-lr release. Ecotoxicol. Environ. Saf. 145:591–596.

Kinley-Baird CM, Smith EF, Calomeni AJ, McQueen AD, Gusler GO, Boyer M, Decker KN, Clyde GA. 2023. Evaluation of preventative algaecide treatments for cyanobacterial resting cells in sediments of a central US lake. Lake and Reservoir Management. 39:340–355.

Kumar A, Maniyar CB, Fiorentino IR, Mishra DR. 2025. Remote sensing of cyanobacterial harmful algal blooms: Current trends and future directions. Prog. Environ. Geogr. 4:131–150.

Kutser T. 2009. Passive optical remote sensing of cyanobacteria and other intense phytoplankton blooms in coastal and inland waters. Int. J. Remote Sens. 30:4401–4425.

Kwon YS, Pyo J, Kwon Y-H, Duan H, Cho KH, Park Y. 2020. Drone-based hyperspectral remote sensing of cyanobacteria using vertical cumulative pigment concentration in a deep reservoir. Remote Sens. Environ. 236:111517.

Legleiter CJ, King TV, Carpenter KD, Hall NC, Mumford AC, Slonecker T, Graham JL, Stengel VG, Simon N, Rosen BH. 2022. Spectral mixture analysis for surveillance of harmful algal blooms (SMASH): A field-, laboratory-, and satellite-based approach to identifying cyanobacteria genera from remotely sensed data. Remote Sens. Environ. 279:953.

Lekki J, Deutsch E, Sayers M, Bosse K, Anderson R, Tokars R, Sawtell R. 2019. Determining remote sensing spatial resolution requirements for the monitoring of harmful algal blooms in the Great Lakes. J. Great Lakes Res. 45:434–443.

Li F, Jupp DLB, Reddy S, Lymburner L, Mueller N, Tan P, Islam A. 2010. An evaluation of the use of atmospheric and BRDF correction to standardize Landsat data. IEEE J. Select. Topics Appl. Earth Observ. Remote Sens. 3:257–270.

Lunetta RS, Schaeffer BA, Stumpf RP, Keith D, Jacobs SA, Murphy MS. 2015. Evaluation of cyanobacteria cell count detection derived from Meris imagery across the eastern USA. Remote Sens. Environ. 157:24–34.

Ma J, Jin S, Li J, He Y, Shang W. 2021. Spatio-temporal variations and driving forces of harmful algal blooms in Chaohu Lake: A multi-source remote sensing approach. Remote Sens. 13:427.

Maguire I, Fitzgerald J, Heery B, Nwankire C, O'Kennedy R, Ducree J, Regan F. 2018. Novel microfluidic analytical sensing platform for the simultaneous detection of three algal toxins in water. ACS Omega 3:6624–6634.

Matthews M. 2017. Bio-optical modeling of phytoplankton chlorophyll-*a*, Chapter 6, pp. 157–188. In: D. R. Mishra, I. Ogashawara, A. A. Gitelson (eds.). Bio-optical Modeling and Remote Sensing of Inland Waters. Cambridge, MA.

McQueen A, Calomeni-Eck A, Kinley-Baird C, Smith EF, Clyde G, Jr., Boyer GL. 2024. Management strategy for overwintering cyanobacteria in sediments contributng to harmful algal blooms (HABS). U.S. Army Engineer Research and Development Center. No. ERDC/TN ANSRP-24-1. Vicksburg, MS.

Michalsen M, Feist S, Vanzomeren C, Seiter-Moser J, Boss A. 2024. USACE freshwater harmful algal bloom research and development initiative. U.S. Army Engineer Research and Development Center. No. ERDC/EL SR-24-1. Vicksburg, MS.

Mishra S, Mishra DR. 2012. Normalized difference chlorophyll index: A novel model for remote estimation of chlorophyll-*a* concentration in turbid productive waters. Remote Sens. Environ. 117:394–406.

Misson B, Latour D. 2011. Influence of light, sediment mixing, temperature and duration of the benthic life phase on the benthic recruitment of microcystis. J. Plankton Res. 34:113–119.

Moore TS, Churnside JH, Sullivan JM, Twardowski MS, Nayak AR, McFarland MN, Stockley ND, Gould RW, Johengen TH, Ruberg SA. 2019. Vertical distributions of blooming cyanobacteria populations in a freshwater lake from Lidar observations. Remote Sens. Environ. 225:347–367.

Moses WJ, Gitelson AA, Berdnikov S, Povazhnyy V. 2009. Estimation of chlorophyll-*a* concentration in case II waters using Modis and Meris data—Successes and challenges. Environ. Res. Lett. 4:045005.

Mullen AL, Watts JD, Rogers BM, Carroll ML, Elder CD, Noomah J, Williams Z, Caraballo-Vega JA, Bredder A, Rickenbaugh E, Levenson E, Cooley SW, Hung JKY, Fiske G, Potter S, Yang Y, Miller CE, Natali SM, Douglas TA, Kyzivat ED. 2023. Using high-resolution satellite imagery and deep learning to track dynamic seasonality in small water bodies. Geophys. Res. Lett. 50:e2022GL102327.

Netherland MD, Schardt JD. 2021. A manager's definition of aquatic plant control. Aquatic Plant Management Society 38809.

[NRC] National Research Council. 2004. Adaptive management for water resources project planning. National Research Council, Washington, DC.

Paerl HW, Huisman J. 2009. Climate change: A catalyst for global expansion of harmful cyanobacterial blooms. Environ. Microbiol. Rep. 1:27–37.

Paerl HW, Paul VJ. 2012. Climate change: Links to global expansion of harmful cyanobacteria. Water Res. 46:1349–1363.

Papenfus M, Schaeffer B, Pollard AI, Loftin K. 2020. Exploring the potential value of satellite remote sensing to monitor chlorophyll-*a* for US lakes and reservoirs. Environ. Monit. Assess. 192:808.

Park Y-J, Ruddick K, Lacroix G. 2010. Detection of algal blooms in European waters based on satellite chlorophyll data from Meris and Modis. Int. J. Remote Sens. 31:6567–6583.

Pokrzywinski K, Morgan C, Bourne S, Reif M, Matheson K, Hammond S. 2021. A novel laboratory method for the detection and identification of cyanobacteria using hyperspectral imaging. U.S. Army Engineer Research and Development Center. No. ERDC/EL TR-21-3. Vicksburg, MS.

Randolph K, Wilson J, Tedesco L, Li L, Pascual DL, Soyeux E. 2008. Hyperspectral remote sensing of cyanobacteria in turbid productive water using optically active pigments, chlorophyll a and phycocyanin. Remote Sens. Environ. 112:4009–4019.

Reynolds N, Schaeffer BA, Guertault L, Nelson NG. 2023. Satellite and in situ cyanobacteria monitoring: Understanding the impact of monitoring frequency on management decisions. J. Hydrol. (Amst.) 619:1–14.

Rolim SBA, Veettil BK, Vieiro AP, Kessler AB, Gonzatti C. 2023. Remote sensing for mapping algal blooms in freshwater lakes: A review. Environ. Sci. Pollut. Res. Int. 30:19602–19616.

Salmaso N, Naselli-Flores L, Padisák J. 2014. Functional classifications and their application in phytoplankton ecology. Freshwater Biol. 60:603–619.

Saltus CL, Reif M, Johansen R. 2022. Water quality for Arcgis pro toolbox: User's guide. U.S. Army Engineer Research and Development Center. No. USACE ERDC/EL SR-22-6. Vicksburg, MS.

Schaeffer B, Loftin K, Stumpf R, Werdell PJ. 2015. Agencies collaborate, develop a cyanobacteria assessment network. Eos Earth Space Sci. News 96.

Schaeffer BA, Reynolds N, Ferriby H, Salls W, Smith D, Johnston JM, Myer M. 2024. Forecasting freshwater cyanobacterial harmful algal blooms for Sentinel-3 satellite resolved U.S. lakes and reservoirs. J. Environ. Manage. 349:119518.

Sentinel Hub. 2024. https://www.sentinel-hub.com/. Sinergise Solutions d.o.o., a Planet Labs company.

Seegers BN, Stumpf RP, Schaeffer BA, Loftin KA, Werdell PJ. 2018. Performance metrics for the assessment of satellite data products: An ocean color case study. Opt. Express. 26:7404–7422.

Shen L, Xu H, Guo X. 2012. Satellite remote sensing of harmful algal blooms (HABS) and a potential synthesized framework. Sensors 12:7778–7803.

Slonecker T, Bufford B, Graham J, Carpenter K, Opstal D, Simon N, Hall N. 2021. Hyperspectral reflectance characteristics of cyanobacteria. Adv. Remote Sens. 10:66–77.

Smucker NJ, Beaulieu JJ, Nietch CT, Young JL. 2021. Increasingly severe cyanobacterial blooms and deep water hypoxia coincide with warming water temperatures in reservoirs. Glob. Chang. Biol. 27:2507–2519.

Stumpf R, Johnson L, Wynne TT, Baker D. 2016a. Forecasting annual cyanobacterial bloom biomass to inform management decisions in Lake Erie. J. Great Lakes Res. 42:1174–1183.

Stumpf RP, Davis TW, Wynne TT, Graham JL, Loftin KA, Johengen TH, Gossiaux D, Palladino D, Burtner A. 2016b. Challenges for mapping cyanotoxin patterns from remote sensing of cyanobacteria. Harmful Algae 54:160–173.

Topp SN, Pavelsky TM, Jensen D, Simard M, Ross MRV. 2020. Research trends in the use of remote sensing for inland water quality science: Moving towards multidisciplinary applications. Water 12:169.

Ussler W, Doucette GJ, Preston CM, Weinstock C, Allaf N, Roman B, Jensen S, Yamahara K, Lingerfelt LA, Mikulski CM, Hobson BW, Kieft B, Raanan BY, Zhang Y, Errera RM, Ruberg SA, Den Uyl PA, Goodwin KD, Soelberg SD, Furlong CE, Birch JM, Scholin CA. 2024. Underway measurement of cyanobacterial microcystins using a surface plasmon resonance sensor on an autonomous underwater vehicle. Limnol. Oceanogr: Methods. 22:681–699.

Verspagen JMH, Snelder EOFM, Visser PM, Huisman J, Mur LR, Ibelings BW. 2004. Recruitment of benthic *Microcystis* (Cyanophyceae) to the water column: Internal buoyancy changes or resuspension? J. Phycol. 40:260–270.

Wang L, Xu M, Liu Y, Liu H, Beck R, Reif M, Emery E, Young J, Wu Q. 2020. Mapping freshwater chlorophyll-*a* concentrations at a regional scale integrating multi-sensor satellite observations with Google Earth engine. Remote Sens. 12:3278.

Wang S, Qin B, 2025. Application of optical remote sensing in harmful algal blooms in lakes: A review. Remote Sens. 17:1381.

Williams B, Szaro R, Shapiro C. 2009. Adaptive management: The U.S. Department of the Interior technical guide. U.S. Department of the Interior, Washington, DC.

Woodcock CE, Loveland TR, Herold M, Bauer ME. 2020. Transitioning from change detection to monitoring with remote sensing: A paradigm shift. Remote Sens. Environ. 238:111558.

Wynne TT, Stumpf RP, Tomlinson MC, Warner RA, Tester PA, Dyble J, Fahnenstiel GL. 2008. Relating spectral shape to cyanobacterial blooms in the Laurentian Great Lakes. International Journal of Remote Sens. 29:3665–3672.

Xu M, Liu H, Beck R, Lekki J, Yang B, Shu S, Liu Y, Benko T, Anderson R, Tokars R, Johansen R, Emery E, Reif M. 2019. Regionally and locally adaptive models for retrieving chlorophyll-a concentration in inland waters from remotely sensed multispectral and hyperspectral imagery. IEEE Trans. Geosci. Remote Sens. 57:4758–4774.

Zhang M, Kong F, Tan X, Yang Z, Cao H, Xing P. 2007. Biochemical, morphological, and genetic variations in *Microcystis aeruginosa* due to colony disaggregation. World J. Microbiol. Biotechnol. 23:663–670.

Zhou T, Li Y, Jiang B, Alatalo JM, Li C, Ni C. 2023. Tracking spatio-temporal dynamics of harmful algal blooms using long-term Modis observations of Chaohu Lake in China from 2000 to 2021. Ecol. Indicat. 146:109842.