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A Review of Sensor-Based Approaches for Monitoring Rapid Response Treatments of cyanoHABs

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A Review of Sensor-Based Approaches for Monitoring Rapid Response Treatments of cyanoHABs

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Final report

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Abstract

Water quality sensors are dynamic and vary greatly both in terms of utility and data acquisition. Data collection can range from single-parameter and one-dimensional to highly complex multiparameter spatiotemporal. Likewise, the analytical and statistical approaches range from relatively simple (e.g., linear regression) to more complex (e.g., artificial neural networks). Therefore, the decision to implement a particular water quality monitoring strategy is dependent upon many factors and varies widely. The purpose of this review was to document the current scientific literature to identify and compile approaches for water quality monitoring as well as statistical methodologies required to analyze and visualize highly diverse spatiotemporal water quality data. The literature review identified two broad categories: (1) sensor-based approaches for monitoring rapid response treatments of cyanobacterial harmful algal blooms (cyanoHABs), and (2) analytical tools and techniques to analyze complex high resolution spatial and temporal water quality data. The ultimate goal of this review is to provide the current state of the science as an array of scalable approaches, spanning from simple and practical to complex and comprehensive, and thus, equipping the US Army Corps of Engineers (USACE) water quality managers with options for technology-analysis combinations that best fit their needs.

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Contents

Figures and Tables

Figures

Tables

Preface

This study was conducted for the Aquatic Nuisance Species Research Program (ANSRP) under 008284, “In-situ evaluation of peroxide treatments applied to harmful cyanobacteria blooms.” At the time of the study, the acting technical monitor was Mr. Michael Greer.

The work was performed by the Environmental Systems Branch of the Ecosystem Evaluation and Engineering Division, US Army Engineer Research and Development Center, Environmental Laboratory (ERDC-EL). Technical reviews and discussions of this report were provided by Ms. Christina Saltus and Dr. Bruce Pruitt of ERDC-EL.

At the time of publication, Mr. Mark R. Graves was chief of the Environmental Systems Branch; Mr. Mark D. Farr was chief of Ecosystem Evaluation and Engineering Division; and Dr. Jennifer Seiter-Moser was technical director for Environmental Engineering and Sciences. The deputy director of ERDC-EL was Dr. Brandon Lafferty, and the director of ERDC-EL was Dr. Edmond J. Russo.

The commander of ERDC was COL Christian Patterson and the director was Dr. David W. Pittman.

1 Introduction

1.1 Background

Cyanobacterial harmful algal blooms (cyanoHABs) remain a complex and persistent problem, adversely impacting water quality globally (Anderson et al. 2012). There are numerous species of cyanobacteria (e.g., blue-green algae), many capable of producing toxic compounds, which can cause harm to humans and wildlife if inhaled or ingested (USEPA 2012). In addition to health concerns, cyanoHABs may result in adverse impacts to local communities, especially those that rely on waterbodies for tourism and fishing (Anderson et al. 2000). Ultimately, it is imperative to develop more long-term, pro-active management strategies that focus on reducing nutrient loading and improving land-use best practices; however, in the short-term there is a critical need for immediate, rapid response control strategies for the US Army Corps of Engineers (USACE) to provide essential services across the US (Matthijs et al. 2012; Geer et al. 2017; Pokrzywinski et al. 2022a).

Currently, there are numerous physical, biological, and chemical approaches to managing cyanoHABs, with each approach varying in cost, level of difficulty, scale, and specificity (Burford et al. 2019). Physical approaches are designed to separate, mix, or sink algae to reduce surface concentrations, and include barriers, oxygenators, and ultrasonic sensors (Beutel and Horne 1999; Lürling and Tolman 2014; Visser et al. 2016). Biological approaches, which can be extremely difficult, focus on disrupting the food-web by targeting algae directly or by limiting nutrients vital for algal growth (Mackay et al. 2014; Mahner et al. 2008). Alternatively, a common management approach using chemicals, such as peroxide-based and copper-based solutions, have been proven to be highly effective in reducing cyanoHABs when used during favorable conditions (Drábková et al. 2007; Matthijs et al. 2012). Given that cyanoHABs are dynamic, found globally, and in waterbodies varying in chemical, biological, and physical characteristics, it is vital that these responsive treatments be evaluated robustly since most of these approaches are still experimental with limited evaluation in the field. For example, the US Environmental Protection Agency (USEPA) registered peroxide-based algaecides that have been shown in lab and pilot studies to be an effective rapid treatment of cyanoHABs. The treatment works almost immediately to decrease cyanoHAB concentrations with no residual environmental impacts (Antoniou et al. 2005; Bauza et al. 2014; Fan et al. 2019; Matthijs et al. 2012). However, due to the limitations of traditional water quality monitoring tools and approaches, real-world applications have not been evaluated at the spatial and temporal resolutions required to comprehensively evaluate the efficacy of these of cyanoHABs mitigation strategies and products. Thus, it is critical for the USACE to develop comprehensive and scalable monitoring efforts to determine the most effective rapid response strategies for mitigating the adverse impacts of cyanoHABs.

1.2 Objective

Due to the rapidly evolving nature of cyanoHAB management, a detailed literature review was required to compile historical and current research on sensor-based approaches for monitoring rapid response treatments of cyanoHABs. The goal is to identify the state of the science through a suite of solutions for water quality monitoring with varying spatial resolutions, temporal coverages, labor/infrastructure costs, and analytical skills required for data processing and interpretation. This review will aid in the planning of operational field campaigns as well as provide insights into novel analytical tools and techniques for evaluating multi-sensor, cross-platform, and complex spatiotemporal data that can be used to monitor and evaluate cyanoHAB treatment efficacy.

1.3 Approach

This report was developed by reviewing and compiling a variety of peer-reviewed scientific articles, government reports, conference proceedings, and theses/dissertations across two major themes: (1) sensor-based approaches for monitoring rapid response treatments of cyanoHABs, and (2) analytical tools and techniques to analyze complex high resolution spatial and temporal water quality data. Initially, articles were compiled using common searchable databases (e.g., Google Scholar, Scopus, Web of science, etc.) and generalizable phrases (e.g., “monitoring cyanobacteria,” “sensors AND harmful algae,” “remote sensing for detecting cyanobacteria,” etc.). Secondly, each piece of literature was individually reviewed to determine if it appropriately addressed at least one of the themes above, with a specific focus placed on literature emphasizing the use of scalable technologies.

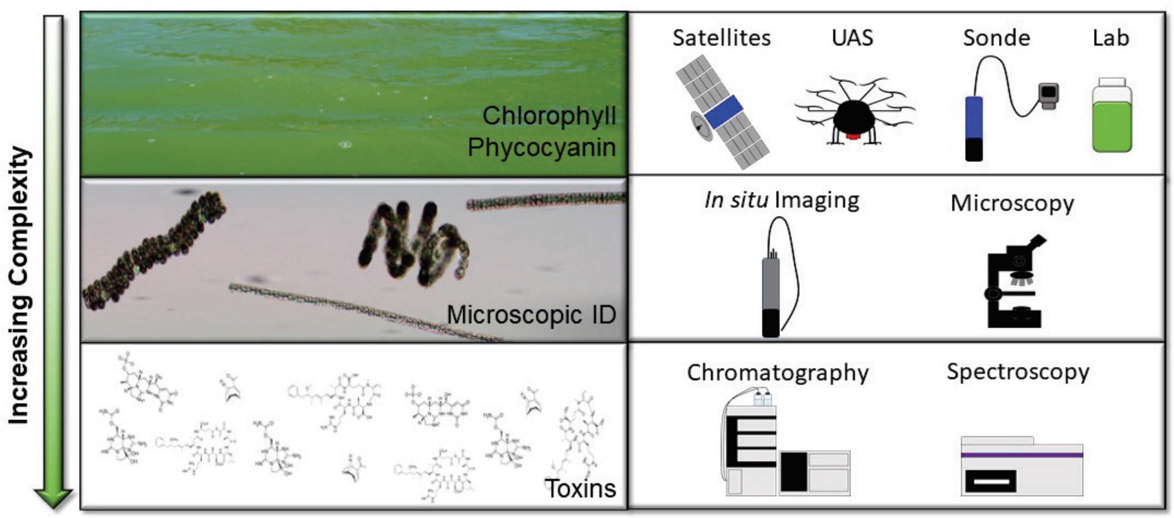
2 Results

2.1 Cyanobacteria data collection methods

A diverse set of tools, technologies, and sensors utilized in the collection of cyanoHAB, and related water quality data were reviewed, including but not limited to the following: field deployable sondes, hand-held optical devices, airborne and satellite-based imagers (Tables 1, 2, and 3). For a more comprehensive list of cyanobacteria detection tools and techniques, see Almuhtaram et al. (2021). Generally, data collection methods can be divided into three broad categories, lab-based, field-based, and remote sensing-based.

Lab-based is the term used for laboratory derived analytical measurements, which utilize specialized equipment such as fluorometer, spectrophotometers, and ELISA kits. Lab-based methods play an important role in cyanoHAB research because they can provide species-level identification (micro-ID) as well as the presence of individual cyanotoxins (Figure 1). These tools and techniques are beyond the scope of this review but are referenced for comparative purposes.

Figure 1. CyanoHAB detection methods.



Field-based methods typically use optical sensors to detect various water quality parameters. Absorbance and fluorescence are the two primary optical detection techniques commonly incorporated into field instruments that can be used as a proxy for cyanobacterial biomass (Pokrzywinski et al. 2022a; Srivastava et al. 2013). This is possible because there is a strong correlation between phycocyanin (PC), the cyanobacteria-specific pigment, fluorescence, and cyanobacterial biomass (Gregor et al. 2007; Lee et al 1994). For example, Asai et al. (2001) compared PC fluorescence to biomass by comparing excitation levels of 620 nanometers (nm) subtracted by the eukaryotic background at 440 nm. As such, the application of field-based sensors (e.g., in situ imagers, sondes) for the monitoring of water quality and detection of cyanoHAB events are now commonplace (Figure 1). Field instruments offer real-time or near real-time measurements of a host of variables critical for assessing water quality, which when deployed, provide water managers with the knowledge to respond more quickly or effectively to impacts by cyanoHABs such as drinking water, recreational activities, and fisheries.

Alternatively, remote sensing-based sensors are commonly used to assess water quality by measuring reflected light energy or solar radiation emitted from the water surface and upper portion of the water column across specific wavelengths of the electromagnetic spectrum. Specifically, the spectral features characteristic of cyanoHABs correspond to key algal biomass indicators including chlorophyll *a* (chl- *a*), PC, and turbidity (Gregor and Marsalek 2004). Key spectral features used in cyanoHAB detection include green reflectance (550 nm), phycocyanin absorption (620 nm), chlorophyll *a* absorption (665 nm - 680 nm), and cell backscattering or turbidity (709 nm) (Davis and Bissett 2007; Kutser 2009; Lekki et al. 2019; Shen et al. 2012; Stumpf et al. 2016). Satellites and airborne sensors are the two main platforms used in remote sensing of water quality, which includes both manned and unmanned aircraft systems (UAS).

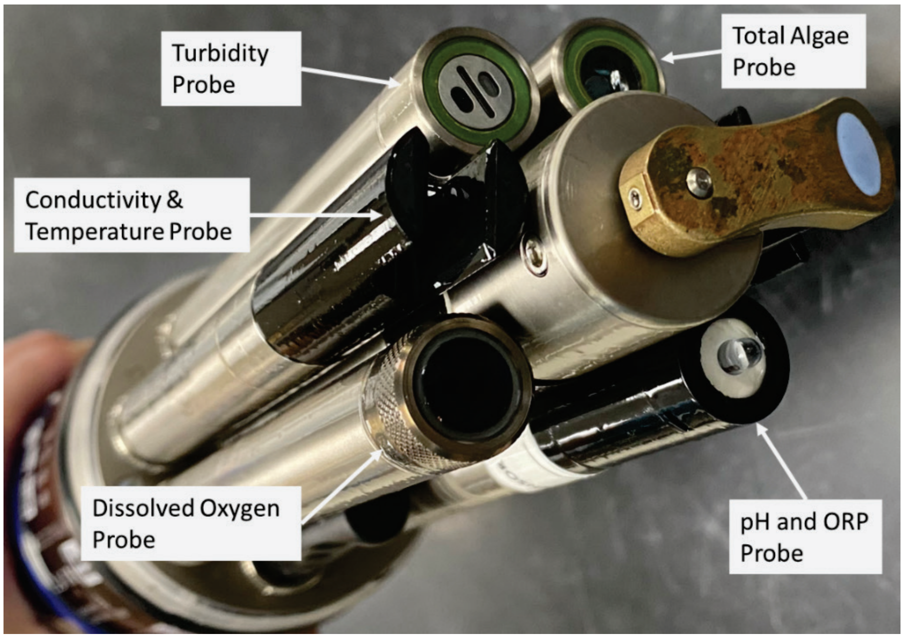
Each of these collection platforms have their own sets of advantages and limitations, including the level of discernable detail (spectral and spatial resolution) and temporal limitations. In this case, detail is considered the specific level of information detectable by a platform or technology. For example, most satellite imagers are only capable of detecting lower-level details such as ubiquitous vegetation pigments (e.g., chlorophyll) and the presence of algae. More sophisticated remote sensing imagers (e.g., hyperspectral sensors) and *in vivo* fluorescence sensors, with their greatly increased spectral resolution, can be used to discern a higher degree of detail including the cyanobacterial-specific pigments, phycocyanin, and delineate between cyanobacterial and other algal genera. For the highest level of detail, such as identifying a particular algal species or toxin, lab-based analytical approaches are still required (Figure 1).

CyanoHAB detection methods range widely in complexity and specificity, less specific techniques, such as remote sensing and water quality sondes, can detect spectrally active pigments (i.e., chl-a and phycocyanin), while more specified lab-based techniques, such as microscopy or chromatography, can identify specific algal species or even individual cyano-toxins.

2.1.1 Optical Field-based sensors

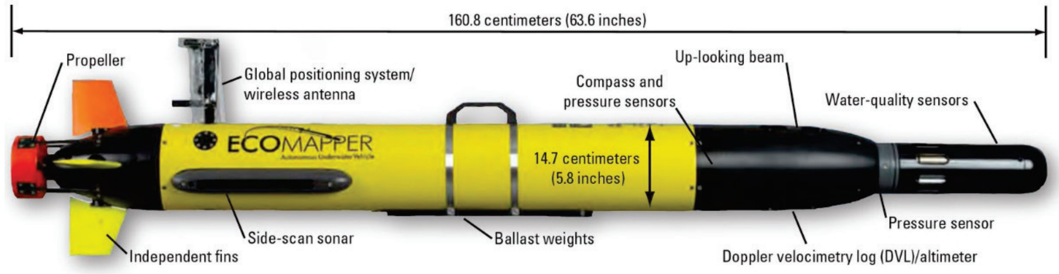
Optical field-based sensors, also referred to as sondes, are water quality devices that consist of ports for interchangeable probes (YSI 2021a) and are commonly used to measure water characteristics, such as temperature, conductivity, dissolved oxygen (DO), turbidity, chl *a*, and PC capable of collecting point data at regular intervals (Figure 2). Sondes offer several advantages over lab-based approaches, such as their ability to collect multi-parameter data continuously at standardized temporal intervals. For more detail on *in vivo* fluorescence probes used for monitoring cyanoHABs, please see Srivastava et al. (2013) for a comprehensive review. Most sondes are fairly lightweight and can also be mounted, submerged, or operated as hand-held units to provide point-based sampling at discrete locations across a waterbody. However, unlike lab-based testing, sondes can also be deployed *in situ* in the field, allowing for routine sampling of a single location for days to months. This flexibility allows for either improved spatial mobility or increased temporal consistency. Currently, typical off-the-shelf sondes tend to be limited to only a handful of sensors (5-7), with probes incapable of providing the resolution given by lab-based methods, such as algal species delineation and cyanotoxin concentrations. Although it should be noted, there has been rapid growth in development of deployable lab-like systems, such as environmental sample processors (ESPs) and Imaging Flowcytobots (IFCBs). For example, the first fresh-water ESP was deployed by NOAA in 2017, designed to detect cyanotoxins in real-time in the Western Basin of Lake Erie (Ritzenhaler et al. 2016). Additionally, IFCBs, which are submersible microscopes equipped with computer vision software, can autonomously and rapidly identify algal species and concentrations (Gandola et al. 2016; Kraft et al. 2021). Although currently, given the cost and/or labor-intensive nature of field-based sensors, most are limited to a few or even a single device per waterbody, which provides limited spatial coverage making it difficult to characterize large areas.

Figure 2. YSI Exo-2 sonde bulkhead with common suite of probes, including Turbidity, Total Algae (e.g., Chlorophyll *a* + Blue-green Algae), Conductivity/Temperature, Dissolved Oxygen (DO), and pH/Oxidation-Reduction Potential (ORP).



In addition to mountable or hand-held instruments, sondes can be attached to autonomous surface/underwater vehicles (ASVs/AUVs), which are an emerging technology being utilized for the monitoring and measuring of water quality (Figure 3). AUVs, such as the EcoMapper i3XO, can generate high-resolution maps of water quality, water currents, bathymetry, and sonar imagery in small inland lakes and reservoirs (Jackson 2013; YSI 2021b). AUVs are deployable at controlled or varying depths for collection of three-dimensional (3-D) near real-time data. AUVs can also provide a high degree of spatial coverage for a waterbody over a limited timeframe. 3-D coverage allows for a comparison of cyanoHAB concentrations and associated variables throughout the water column, not just at the surface (remote sensing) or at a single location (sondes). The ability to monitor short-term bloom movement will improve monitoring and predictive efforts used to provide warnings for local tourism and fishing industries. In addition, understanding fine-scale environmental conditions associated with bloom formation will increase our ability to predict the location and timing of bloom formation (Robbins et al. 2006).

Figure 3. Diagram of the YSI EcoMapper Autonomous Underwater Vehicle (AUV). USGS 2020. Public Domain



Additionally, there are handheld optically based tools, such as spectroradiometers, which are designed to measure the radiance, amplitude, and direction of electromagnetic radiation of an object at close proximity. A typical spectroradiometer, contains numerous narrow spectral brands (1 nm–3 nm) covering the visible near infrared (350 nm–1000 nm) and thermal bands (1000 nm -2500 nm) of the electromagnetic spectrum (Malvern Panalytical 2021). The high spectral resolution of these sensors allows for the development of optically derived cyanoHAB algorithms by detecting water quality related indicators, such as chl *a* (Rundquist et al. 1996), PC (Bowling et al. 2017), and turbidity (Han 1996). Additionally, spectroradiometers are commonly used for validating airborne and satellite remote sensing algorithms, which are applied to the imagery for estimating water quality indicators (Beck et al. 2016; Shen et al 2012; Wang et al 2020).

Table 1. Common and emerging field-based sensors for CyanoHAB detection and monitoring.

Instrument	Application	CyanoHAB Parameters	Example
Sondes	Handheld, Deployable, Mountable	Algal Pigments Turbidity Water characteristics (Temp, DO, pH)	YSI Exo2 Sonde
AUVs	Deployable	Algal Pigments Turbidity Water characteristics (Temp, DO, pH)	YSI EcoMapper i3 XO
Environmental Sample Processor (ESPs)	Deployable	Cyanotoxins	NOAA ESP
Imaging Flowcytoobots (IFCBs)	Deployable	Algal species, Biomass	McLane IFCB
Spectroradiometers	Handheld	Algal pigments, Algal Genera	ASD FieldSpec

2.1.2 Satellite remote sensing

Satellite-based earth observing (EO) sensors are now used ubiquitously for the monitoring and detection of natural and anthropogenic phenomena on the Earth's surface. Many of the first satellite sensors were designed for large (100-1000s of km^2) terrestrial or meteorological applications (e.g., national land cover, storm tracking), and as technology has improved, more specialized sensors have emerged. Of particular interest to this research, technological improvements have enabled water quality applications as it relates to the increasing frequency of eutrophication and cyanoHAB events (Wells et al. 2020). Spectrally derived algorithms can then be developed, such as the normalized difference chlorophyll index, or NDCI, which can be used to detect and quantify key HAB and cyanoHAB indicators, namely chl-*a*, PC, and turbidity (Beck et al. 2016; Johansen et al. 2019; Mishra et al. 2014; Randolph et al. 2008; Simis et al. 2005; Stumpf et al. 2016; Wynne et al. 2008). While most satellite multispectral sensors (MSS) were designed for large-scale terrestrial applications and have only a few wide spectral bands (~100-200 nms), there are a handful of MSS with the spatial, spectral, and temporal resolutions appropriate for monitoring water quality of small inland water bodies (e.g., Moderate Resolution Imaging Spectroradiometer [MODIS], Landsat-8 Operational Land Imager [LS8 OLI), WorldView-2 MSI [WV2 MSI], WorldView-3 [WV3 MSI] Sentinel-2 MSI [S2 MSI], Medium-Spectral Resolution Imaging Spectrometer [MERIS], and Sentinel-3's Ocean and Land Colour Instrument [OLCI]). However, each sensor has their own trade-offs between spatial, spectral, and temporal coverage (Table 2).

Table 2. Satellite imager resolutions.

Satellite-Sensor	Spatial Resolution	Key Spectral Resolution	Temporal Resolution
WorldView-2 MSI (2009 – Present)	1.8 m	Bands: 6 Range: 400 nm–725 nm Bandwidths: 40-70 nm	1-2 days
Sentinel-2 MSI (2016 – Present)	20 m	Bands: 8 Range: 443 nm–865 nm Bandwidths: 15-65 nm	5 days
Landsat-8 OLI (2013 – Present)	30 m	Bands: 5 Range: 443 nm–865 nm Bandwidths: 20-60 nm	16 days

Satellite-Sensor	Spatial Resolution	Key Spectral Resolution	Temporal Resolution
MODIS (High Spatial) (1999 – Present)	250-500 m	Bands: 4 Range: 469 nm–858 nm Bandwidths: 20-50 nm	1-2 days
MODIS (Low Spatial) (1999 – Present)	1000 m	Bands: 12 Range: 412 nm–940 nm Bandwidths: 10-50 nm	1-2 days
MERIS (2002 – 2012) OLCI (2016 – Present)	300 m	Bands: 21 Range: 400 nm–1020 nm Bandwidths: 3-40 nm	1-2 days

Legend	Good	Moderate	Poor

*A list of satellite imagers and qualitative rankings (good [green], moderate [yellow], poor [orange]) of each sensor's inherit spatial, spectral, and temporal resolutions as it relates to the effectiveness to detect cyanoHABs.

2.1.3 Airborne remote sensing

For this review, airborne remote sensing refers to both manned (e.g., planes) and unmanned aircraft systems (e.g., UAS). Manned airborne missions, while generally cost-prohibitive for frequent routine monitoring needed for water quality, offer unique capabilities for testing pre-launch satellite-based imagers or for validating satellite-based imagery (Beck et al. 2016; Lekki et al. 2019). More recently, there has been dramatic improvement to both sensors and platforms, including increased payload capacity and cost reduction, which has led to an increased focus on UAS-based remote sensing research. This is because small UAS platforms, as designated under the Federal Aviation Administration's (FAA) 14 CFR part 107, offer some potential advantages over both satellite remote sensing and manned aircraft, including increased operational flexibility during surveys. Given the low flying altitudes, UAS platforms are much less affected by atmospheric conditions – but can be more impacted by localized weather conditions, including wind. Additionally, UAS platforms have spatial resolutions much finer than satellite imaging sensors, allowing for the detailed monitoring of highly targeted areas of interest, such as swim beaches, water intakes, or shorelines. Although there are no commercial "off-the-shelf" UAS platforms specifically designed for detecting cyanoHABs, the correct combination of platform and commercially available sensors can provide a unique opportunity to examine cyanobacteria and water quality at scales not possible with operational satellite imagers (Table 3). Additionally, UAS platforms can play a pivotal role in bridging the gap between traditional remote sensing and field-based monitoring (Castro et al. 2020; Pokrzywinski et al. 2022b).

Table 3. Sample list of commercially available imagers used for cyanHAB monitoring.

Sensor	Platform	Spectral Range	Reference
Headwall Photonics HSI	UAS	400 – 1000 nm	1. Pokrzywinski et al. 2022b
CASI-1500 HSI	Airborne	367 nm – 1047 nm	1. Beck et al. 2016 2. Johansen et al. 2019
MicaSense RedEdge	UAS	5-band (VNIR)	1. Castro et al. 2020 2. Green, LeFevre, and Markfort 2021

2.2 Analytical methods for evaluating water quality

There are countless numbers of statistical techniques for modeling and estimating water quality. Given the immensity of statistical choices, a high-level overview of commonly utilized approaches for modeling water quality through four general types of data collection methodologies, conventional (univariate), multivariate, spatiotemporal, and remote sensing are presented (Table 4). This review is not meant to be exhaustive, nor does it suggest that statistical approaches are exclusive to a particular data collection method. However, the goal was to compile the most common approaches for analyzing diverse datasets acquired from a variety of collection strategies described in the previous sections. It is important to note that statistical approaches must be viewed in context to its biological relevance when interpreting the results of any analysis.

2.2.1 Conventional (univariate) statistics

For this review, the term "conventional" is used for any in situ or in vivo measurement collected at a single point in space and time. It is important to note, that although the focus of this review remains on sensor-based tools and analyses, these statistics are commonly applied to lab-based grab samples too. A range of statistical tests can be applied to water quality data for a variety of experimental scenarios: (1) Analysis of variance (ANOVA), repeated-measures (RM-ANOVA), or Tukey's Post Hoc test for intrawater body comparisons, or (2) Nonparametric Mann-Whitney test for interwaterbody differences (Barrington and Ghadouani 2008; Bauzá et al. 2014; Pokrzywinski et al. 2022a; Sinha et al. 2018). These approaches can also be used to assess bulk changes in measured variables (i.e., chlorophyll *a*, phycocyanin, turbidity, etc.) following algicide treatment at a single time point or over time (repeated measures).

2.2.2 Multivariate statistics

In addition to conventional univariate statistics, numerous multivariate approaches have been utilized in cyanoHAB and water quality research. Notable contributions include the following:

- Plymouth Routines in Multivariate Ecological Research (PRIMER-e)-derived multivariate routines in a two-dimensional space

  Grouping (cluster analysis)
  Sorting (non-metric multidimensional scaling [nMDS])
  Principal component analysis (PCA)
  Hypothesis testing (permutational multivariate analysis of variance [PERMANOVA]
  Analysis of similarities [ANOSIM], etc.)
  Correlations (linking biotic patterns to environmental variables [BEST])

- Global analyses to calculate a "global" best fit indicator generated from multiple water quality variables
- Least significant difference (LSD) used to perform multiple pairwise comparisons across time and peroxide treatments (Fan et al. 2019; Huang and Zimba 2020).

Rousso et al. (2020) provides a comprehensive review of forecasting and predictive cyanoHAB models, containing dozens of process-based and data-driven statistical approaches linked to numerous water quality indicators and predictors associated with cyanobacterial dynamics. These approaches can be used to match community-level information like abundance, presence/absence, and percent cover with physical and chemical water properties to identify drivers of HAB events or relationships between variables that could be used as indicators for bloom events. It could also be used to examine community-level changes following algicide treatment and may be useful for identify HAB susceptible systems and in restoration efforts to identify healthy algal communities.

2.2.3 Spatio-temporal data analyses

As more continuous sensors are deployed and connected via the internet of things (IoT), it would be logical to expect a growing demand for near real-time high-resolution spatiotemporal data to be utilized for the visualization and analysis of water quality and cyanoHAB dynamics. In the literature, some research has expanded traditional statistical approaches to explore spatial and temporal change, such as multivariate analysis of variance (MANOVA), principal components analysis (PCA), nMDS/MDS, and spatial autocorrelation using Moran's I (Eneji et al. 2012; Rohaizat and Khanan 2018; Nong et al. 2019). Even with the expansion of deployed sensors, interpolation and extrapolation will be required to modeling entire water bodies. Vizcaíno et al. (2016) utilized a k-nearest neighbor (k-NN) approach to conduct a non-uniform spatio-temporal analyses of water quality designed to provide a more rigorous interpolation than traditional methods. In addition to advancing analytical methods and statistical approaches, there has been significant advances in the use of ASVs for the collection of multiple coincident water parameters and cyanoHAB indicators at high spatial and temporal resolutions within a waterbody (Robbins et al. 2006; Jackson 2013). These data can be aggregated both spatially and temporally into spatiotemporal data sets, also known as space-time cubes, which can be visualized and analyzed by applying analytical tools such as emerging hot spot analysis or time series clustering available in commonly used geographical information system (GIS) software packages.

2.2.4 Remote sensing models

Remote sensing, spectrally derived models, are traditionally correlated to some *in situ* and *in vivo* ground-based measurements and broken into three broad categories: empirical, semiempirical/semianalytical, and analytical. Empirically based algorithms correlate the values of remote sensing imagery pixels to ground measured water quality constituents (Dekker 1993; Mittenzwey et al. 1992; Olmanson et al. 2011). While analytical algorithms spectrally partition a specific HAB pigment or water quality constituent from the water's remaining inherit optical properties (IOPs) such as absorption, particulate scattering, and backscattering (Dekker et al. 2001). The last category of algorithms, semi-empirical or semi-analytical, apply a combination of both empirical and analytical approaches, by optimizing an empirical model with the use of one or more IOPs (Gons 1999; Gons et al. 2002; Simis et al. 2005). It is important to note that analytical and semi-empirical/semi-analytical algorithms require localized knowledge of a specific waterbody's IOPs, which make them more complex and less portable because they are derived for a particular source of water.

The review by Matthews (2011) demonstrates the variety of statistical approaches that can be applied to modeling water quality with remote sensing imagery. He compiled dozens of water quality algorithms which use nineteen different statistical approaches ranging from common ones like linear regression analysis to more complex techniques like artificial neural network. Recently, the use of advanced autonomous vehicles for water quality monitoring and modeling has been increasing. For example, improvements in UAS coupled with hyperspectral sensors have begun to advance water quality monitoring efforts, especially regarding algal species-level detection and estimation (Lyu et al. 2016; Castro et al. 2020; Pokrzywinski et al. 2022b).

Table 4. Summary of analytical categories used for water quality evaluation

Analytical Category	Sensor	Data Type	Spatial	Level of Effort	Example
Conventional (Univariate)	Sondes, ESPs, IFCBs	Point	1-D	Low	Determine change in phycocyanin concentration after treatment
Multivariate	Sonde, ESPs, IFCBs	Point, Matrix, Time Series	1-D, 2-D	Medium	Generate predicative models using multiple water quality indicators
Spatio-Temporal	Sonde, ESPs, IFCBs	Matrix, Time Series, Imagery	2-D, 3-D, 4-D	High	Calculate cyanoHAB concentration changes over an entire bloom cycle
Remote Sensing	Optical Imagers, Spectroradiometers	Raster, Spectra, Time Series	2-D, 3-D, 4-D	High	Map of surface Chl *a* concentration for entire waterbody

3 Conclusions

CyanoHABs remain a global problem which will require more robust long-term mitigation strategies. However, in the short-term, water quality managers will have to rely on increased monitoring campaigns coupled with short-term rapid response programs, such as peroxide-based treatments. This review explores the current literature for scalable technologies capable of monitoring water quality and HAB-related indicators.

Generally, there are two approaches to monitoring cyanoHABs, field-based sensors and remote sensing tools. With the advancement in technology and computational power and the ever-growing IoT, it is reasonable to believe that water quality monitoring will be dominated by networks of smart sensors. However, most of these devices are still in their infancy and remain cost-prohibitive for practical purposes, so there is still a reliance on a multi-prong approach. For instance, remote sensing remains an effective regional approach, while point-based lab samples are required for toxin analyses.

In addition, this review provides a compilation of various analytical and statistical approaches that can be applied to data acquired from a variety of technologies, with the goal of exploring new applications for high resolution spatiotemporal monitoring of water quality and cyanoHAB treatment efficacies. Analytical approaches to analyze these data are extremely variable, from relatively simple ANOVA or linear regression approaches to more complex procedures involving artificial intelligence (PCA, neural networks, etc.); however, there are still limited research tools available to monitor and analyze high spatial and temporal water quality data. This review presents a series of sensor-based approaches to monitor and quantify cyanoHABs, from the basic to the complex and comprehensive to provide USACE water quality managers with scalable options for technology-analysis combinations. Additionally, these technology-analysis combinations directly support USACE efforts to evaluate the efficacy of peroxide as a rapid response treatment for cyanoHABs.

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14. ABSTRACT
Water quality sensors are dynamic and vary greatly both in terms of utility and data acquisition. Data collection can range from single-parameter and one-dimensional to highly complex multiparameter spatiotemporal. Likewise, the analytical and statistical approaches range from relatively simple (e.g., linear regression) to more complex (e.g., artificial neural networks). Therefore, the decision to implement a particular water quality monitoring strategy is dependent upon many factors and varies widely. The purpose of this review was to document the current scientific literature to identify and compile approaches for water quality monitoring as well as statistical methodologies required to analyze and visualize highly diverse spatiotemporal water quality data. The literature review identified two broad categories: (1) sensor-based approaches for monitoring rapid response treatments of cyanobacterial harmful algal blooms (cyanoHABs), and (2) analytical tools and techniques to analyze complex high resolution spatial and temporal water quality data. The ultimate goal of this review is to provide the current state of the science as an array of scalable approaches, spanning from simple and practical to complex and comprehensive, and thus, equipping the US Army Corps of Engineers (USACE) water quality managers with options for technology-analysis combinations that best fit their needs.

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