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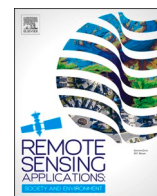
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A review on remote-sensing-based harmful cyanobacterial bloom monitoring services

Nasim Janatian^{a,b,*}, Urmas Raudsepp^b, Parya Broomandi^{c,d}, Kate Fickas^e, Kalle Olli^{f,g}, Timo Heimovaara^a, Aarne Mannik^b, Rivo Uiboupin^b, Nima Pahlevan^h

^a Delft University of Technology, Faculty of Civil Engineering and Geosciences, Department of Geoscience & Engineering, Stevinweg 1, 2628 CN, Delft, Netherlands

^b Department of Marine Systems, Tallinn University of Technology, Akadeemia tee 15a, 12618, Tallinn, Estonia

^c Department of Civil and Environmental Engineering, School of Engineering and Digital Sciences, Nazarbayev University, Astana, 010000, Kazakhstan

^d Department of Electrical and Computer Engineering, School of Engineering and Digital Sciences, Nazarbayev University, Astana, 010000, Kazakhstan

^e Environmental Systems Research Institute, Redlands, CA, 92373, USA

^f Institute of Ecology and Earth Sciences, University of Tartu, Tartu, Estonia, Liivi 2, Tartu, 50409, Estonia

^g Centre for Limnology, Institute of Agricultural and Environmental Sciences, Estonian University of Life Sciences, Tartu, Estonia, Kreutzwaldi 5, Tartu, 51006, Estonia

^h Earth Science Division, NASA Headquarters, 300 E St SW, Washington DC, D.C., 20546, USA

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ABSTRACT

Optical satellite observations have been recently introduced as the backbone of several harmful algal bloom monitoring frameworks for regional or continental-scale decision-making. Documented in prior peer-reviewed publications, these satellite-based decision support systems are not directly comparable, making a synthesis effort inevitable for future improvements. This review highlights select, widely used harmful cyanobacteria bloom (cyanoHABs) monitoring services, including the Cyanobacteria Assessment Network (CyAN), Cyanobacterial Bloom Indicator (CyaBI), CyanoTRACKER, EOLakeWatch, and CyanoKhoj, by focusing on their effectiveness in freshwater and inland waters. We selected these systems for their widespread use, documented effectiveness, and diverse approaches to cyanoHABs monitoring. These services provide early warnings and actionable insights, enabling effective responses to protect water quality, ecosystem health, and public safety. It considers the broader remote-sensing-based monitoring landscape, noting the capabilities and impacts of these services. Our assessments underscore the transformative impact of services like CyAN, which provide robust early warnings using the Cyanobacteria Index (CI). CyanoTRACKER and EOLakeWatch improve community engagement and data collection, increasing monitoring effectiveness. CyanoKhoj leverages high-resolution monitoring through GEE, offering valuable insights. The quality of cyanoHABs products depends on satellite imagery and processing level, noting that most processors leverage Top of Atmosphere or Rayleigh-corrected reflectance products to arrive at cyanoHABs products. Challenges in cyanoHABs monitoring also include variability in ecosystems and accurate biomass estimations. Despite challenges, services like CyAN, CyanoTRACKER, EOLakeWatch, and CyanoKhoj have made significant strides in communicating and managing cyanoHABs risks. This review identifies key future research directions: (1) improving algorithmic approaches and accuracy, (2) defining a

* Corresponding author. Department of Geoscience & Engineering, Delft University of Technology, Stevinweg 1, 2628 CN, Delft, the Netherlands.
E-mail address: nasimjntn@gmail.com (N. Janatian).

universal threshold for bloom formation, (3) utilizing emerging technologies and democratizing data and information, and (4) addressing satellite technique trade-offs in cyanoHABs analysis. By focusing on these areas and leveraging machine learning, future advancements promise more accurate and comprehensive monitoring to protect aquatic ecosystems and public health.

Abbreviations

%NRMSE	percentage Normalized λ Root Mean Squared Error
AC	Atmospheric correction
CCD	cyanobacteria cell density or cyanoHABs abundance
Chla	Chlorophyll- <i>a</i>
CI	Cyanobacteria Index
CyanoHABs	Cyanobacterial harmful algae blooms
GEE	Google Earth Engine
HAB	Harmful algae blooms
MODIS	Moderate Resolution Imaging Spectroradiometer
MSI	Multi-Spectral Instrument
NDCI	Normalized Difference Chlorophyll Index
NIR	Near-infrared
red-NIR	red and NIR bands
OLCI	Ocean and Land Colour Instrument
PC	Phycocyanin
RS	Remote Sensing
SS (λ)	The spectral shape at (λ) nm

1. Introduction

The term “trophic”, derived from the Greek word for nourishment, plays a pivotal role in ecology, describing the relative flux rate of carbon (C) into the food chain (Odum, 1956). Trophic status is a concept that addresses the idea of an ecosystem’s potential food base, a core characteristic in the understanding of ecological structures (Odum, 1956; Lindeman, 1942).

Trophic state varies across a spectrum, from oligotrophic, or unproductive, to hypereutrophic, characterized by high productivity (Lyche Solheim et al., 2023; Beaulieu et al., 2019; Dodds, 2007). These conditions are shaped by both anthropogenic activities and ecosystem structure, both of which significantly influence water quality. One of the most critical issues affecting water quality and trophic status globally is eutrophication pressure, which results from high levels of nutrients in the water, particularly nitrogen and phosphorus. Eutrophication pressure poses a substantial threat to the quality of inland and fresh waters worldwide and has the potential to inflict lasting damage to aquatic ecosystems (Suresh et al., 2023; Lewis et al., 2011; Steffen et al., 2015). The continued alteration in the occurrence and severity of extreme weather events, largely driven by climate change (Mishra, 2023; Sage, 2020), together with increased eutrophication, often triggers the emergence of harmful algal blooms (HABs) (Griffith and Gobler, 2020). CyanoHABs are a form of freshwater phytoplankton bloom that cause harm to human life and are considered a significant worldwide issue in marine, inland, and freshwater ecosystems (Gobler, 2020; Hallegraeff, 1993; Zohdi and Abbaspour, 2019). Notably, there is a strong link between cyanoHABs and eutrophication (Anderson et al., 2021; Glibert et al., 2008; le Moal et al., 2019), and the presence of cyanoHABs in freshwater and inland waters are widely accepted as an indicator of eutrophication (Howard et al., 2023; Wurtsbaugh et al., 2019; Benayache et al., 2019a), underlining the pressing need to address this global environmental challenge.

HABs reduce water column transparency and harm aquatic organisms and the primary ecological structure and function of water bodies (Metcalfe et al., 2021; Tarafdar et al., 2021). Further, some harmful cyanobacteria (e.g., *Microcystis* spp., *Anabaena* spp.) can produce toxins, endangering human life and health (Harke et al., 2016; Halinen et al., 2007). Despite the general classification of cyanoHABs as toxic or non-toxic, both can cause harm (Bricker et al., 2008; Hallegraeff et al., 2021a,b; Pitcher and Calder, 2010). The severity of the harm mainly relates to the magnitude of the bloom and the presence of toxin-producing phytoplankton species, leading to deteriorated water quality and health hazards (Benayache et al., 2019b; Hudnell, 2008; Lopez et al., 2008). CyanoHABs events can cause a variety of negative consequences for both ecosystem and public health. Environmental impacts include hypoxia or anoxia and significant risk to the diversity of aquatic life. Public health concerns include increased water treatment costs for drinking water and economic damages to commercial fishing and tourism (Binding et al., 2021; Stumpf et al., 2012; Watson et al., 2016).

The pace of global warming is predicted to have significant environmental consequences, including increased frequency of extreme weather events, atmospheric stilling (Zhang et al., 2019; Woolway et al., 2017; Janatian et al., 2020), heat waves, windstorms, droughts, and unexpected severe rainfalls (Jeppesen et al., 2021). These changes in extreme weather events and their characteristics, such as intensity, frequency, and duration, are attributed to human-induced global warming and climate change (Jeppesen et al., 2021;

Chidammodzi and Muhandiki, 2015). Extreme weather events threaten the patterns, magnitude, and distribution of cyanoHABs in freshwater and inland environments (Gao et al., 2021; Gobler, 2020). Shifts in climate-driven factors can lead to significant changes in aquatic ecosystems (Wang et al., 2023a). These changes may result in cyanoHABs species gaining a competitive advantage over non-HAB species within plankton assemblages. Furthermore, these climate shifts could spur increased toxin production by cyanoHABs species and the alteration of hydrological patterns, such as amplified surface runoff and flooding, also contribute to an increased likelihood and magnitude of biomass growth of cyanoHABs (Wells et al., 2020; Brooks et al., 2016; Phlips et al., 2020; Wang et al., 2023b). The growing occurrence of cyanoHABs on a global scale has become a significant concern (Hallegraeff et al., 2021a,b). Their prevalence poses severe risks, as they are influenced by eutrophication, rising atmospheric carbon dioxide (CO₂) levels, and ongoing global warming trends (Johnk et al., 2008; Shi et al., 2019; Miller et al., 2017). It is critical to employ accurate cyanoHABs monitoring as it forms the cornerstone of their scope, shedding light on the full magnitude and implications of their dynamics. Monitoring and measuring cyanoHABs with traditional field sampling method and lab analyses, can be laborious, time-consuming, and expensive while providing limited spatiotemporal coverage (Binding et al., 2019, 2021; Dove and Chapra, 2015; Kratzer et al., 2019). As a result, there can be high uncertainty in detecting and characterizing cyanoHABs events of varying magnitudes (Ekstrom et al., 2020; Loisel et al., 2017; Werdell et al., 2009). Satellite-based monitoring offers a cost-effective and rapid solution to these challenges (Barruffa et al., 2021; Loukas et al., 2018). Therefore, it becomes imperative that we expand our efforts in advancing satellite-based research for the detection, characterization, quantification, and monitoring of cyanoHABs. This enhanced focus is essential not only for our understanding, but to provide decision makers with the most comprehensive and accurate data, enabling them to make informed, timely decisions about ecosystem and public health (Barruffa et al., 2021; Gholami et al., 2019; Tirado et al., 2010).

Driven by the urgent need to protect our water resources and ensure public health, this study sets out to critically examine the current state of satellite-based cyanoHABs monitoring services. This work aims to synthesize available information and disseminate knowledge about services within freshwater communities. It seeks to equip these communities with cutting-edge knowledge to respond effectively to these increasing events. Looking broader than just natural resource management, this study aspires to serve as an essential resource for all interested in understanding the present state of knowledge of satellite-based cyanoHABs monitoring, current shortcomings, and potential avenues for future research. Specifically, we aim to 1) outline the features of different available cyanoHABs services, 2) explain their limitations and benefits, and their socioeconomic impacts, and 3) highlight the prospective services born out of more advanced missions and products in the future. This introduction prepares readers for discussions on satellite-based cyanoHABs monitoring, enhancing understanding of its current state and future potential. Following this introduction, the paper is structured as follows: section 2 offers a foundational understanding necessary for grasping the complexities of cyanoHABs, followed by section 3 focused on satellite-derived cyanoHABs detection applications and their characteristics. Our review continues with section 4, which entails the socioeconomic benefits of cyanoHABs services, and ends with future research directions in section 5. As such, a review and compilation of these services' features, strengths, and weaknesses can promote collaboration among Earth observation scientists, space agencies, operational users, policymakers, resource managers, and other stakeholders dealing with cyanoHABs, all striving towards better protection of water bodies and public health (Schaeffer et al., 2013, 2018).

Concluding our introduction, we simplify cyanoHABs monitoring for stakeholders by highlighting methodologies and impacts, making the science accessible for informed decision-making in cyanoHABs management and mitigation.

2. Background

Traditional approaches to cyanoHABs monitoring typically involve field-based data and sample collection and subsequent laboratory analysis (Binding et al., 2019, 2021; Chaffin et al., 2021; Dove and Chapra, 2015; Kratzer et al., 2019). Traditional field-based harmful cyanobacteria detection methods rely on morphological structure-based detection, which can offer insights into species composition and abundance, including cell density (Barkallah et al., 2020). Microscopic examination and image identification techniques represent two common methods used for monitoring cyanoHABs (Barkallah et al., 2020; Liu et al., 2022a). Among the various methods, cytochrome-based detection methods, such as high-performance liquid chromatography (Mackey et al., 1996; Yu et al., 2021) and immunoassays like ELISA (Jaria et al., 2020) are key examples of advanced cyanoHABs monitoring techniques, focusing on pigment and antibody analysis, respectively. Additionally, methods like polymerase chain reaction (Liu et al., 2022b) represent nucleic acid-based approaches.

Generally, cyanoHABs contain phytoplankton cells that exhibit unique optical characteristics, including absorption, scattering, and fluorescence, which serve as insightful indicators of algal cell size, shape, and intracellular components (Busch, 2013). Despite progress, there are still challenges in extracting distinct optical signatures from these aggregate signals, especially when the species of interest must constitute a substantial portion of the total phytoplankton biomass. Specialized sensors, such as fluorometers, measure the fluorescence signal produced by phytoplankton pigments in situ, utilizing pigment signatures without pigment extraction. These sensors serve as the basis for most bio-optical methods in detecting cyanoHABs in water bodies (Valente et al., 2019; Roy et al., 2011). On the other hand, laboratory analysis of pigments such as phycocyanin, which involves physical extraction and chemical processes, can be more challenging and costly (Zamyadi et al., 2016). Fluorometers provide real-time measurements in the field, while laboratory extraction applies for more detailed pigment quantification. However, cyanobacteria, a prokaryotic phytoplankton group, has two primary pigments, phycocyanin (PC) and chlorophyll *a* (Chl*a*), that serve as proxies for biomass in water bodies. The distinct absorption peaks for Chl*a* and PC are as follows: 1) Chl*a* peak is at ~443 and ~670 nm (Gons, 1999), and 2) PC absorption peak is between 550 nm and 650 nm (Richardson, 1996b) with the highest absorption around 615 nm (orange-red light) (Anderson et al., 2015; Simis et al., 2005). Chl*a* is a common biomass metric with routine standard laboratory techniques (Trees et al., 1985). PC is rarely measured and requires more complex, and often more expensive (McQuaid et al., 2011; Kasinak et al., 2015) laboratory

techniques (Lawrenz et al., 2011); thus, extracting its pigment from cells is complex. The presence and abundance of PC further depend on species composition, light availability, nutrient availability, and physiological condition of organisms (de Marsac, 2003). Chla serves as a superior optical surrogate when cyanobacteria are the dominant species, whereas phycocyanin (PC) is recommended when the blooms consist of a diverse mix in which cyanobacteria are not dominant (Stumpf et al., 2012). However, cyanoHABs monitoring is predicated on the discernment of Chla and PC spectral signatures, which is integral to accurately identifying cyanobacterial dominance. This step is vital to prevent overlap in Chla absorption peaks with PC once bulk phytoplankton absorption spectra are analyzed (Dekker et al., 1991; Khan et al., 2021; Kutser, 2004).

Field-based cyanoHABs detection methods, despite their importance, offer only a partial-scale spatial and temporal coverage of bloom events. This limitation contributes to the uncertainty in fully grasping the onset, progression, and resolution of cyanoHABs events (Ekstrom et al., 2020; Loisel et al., 2017; Werdell et al., 2009). Emerging technologies such as automatic high-frequency monitoring systems (HFM) offer real-time data to enhance monitoring but encounter costs, sensor maintenance, and data management obstacles (Reynolds et al., 2023). As such, there is a pressing demand for effective monitoring strategies of cyanoHABs spatiotemporal dynamics in freshwater and inland water bodies.

Today, Earth observation satellites stand as an invaluable resource for aquatic ecosystem monitoring, offering unprecedented spatiotemporal coverage and reach, even into the most remote corners of our planet. (Bracher et al., 2017; Donlon et al., 2012a; Groom et al., 2019). Following the launch of multiple operational satellites over the last decade, Earth observation products have been pivotal in monitoring aquatic ecosystems and developing research, policy, and management strategies (Alikas et al., 2010; Ho et al., 2019; Simis et al., 2005).

The utility of RS products for monitoring cyanoHABs, including their intensity (Bullerjahn et al., 2016; Donlon et al., 2012), extent (Coffer et al., 2021; Urquhart et al., 2017), and frequency (Clark et al., 2017), has increased in popularity over the past few decades. Global imagers with coarse spatial resolutions (up to 1 km), such as the Moderate Resolution Imaging Spectroradiometer (MODIS), have been particularly useful for cyanoHABs monitoring in coastal and open-ocean environments (Toming et al., 2017). Recent advances in cyanoHABs monitoring emphasize the significant role of RS technologies in overcoming traditional limitations. For instance, Qiu et al. (2025) developed an integrated framework that combines space-based remote sensing, aerial platforms, and ground-based methods to achieve multi-scale, high-frequency monitoring of cyanoHABs in eutrophic lakes. This framework used RS sensing products to track bloom dynamics across space and time, leading to improved accuracy of monitoring and early warning systems. Similarly, Qiu et al. (2023) incorporated the same satellite products into a collaborative approach that relied on land-based video monitoring to focus on nearshore areas. They accurately predicted accumulation risks in vulnerable zones like water intakes by integrating RS data with land-based video monitoring and dynamic environmental indices like Chla. This approach addressed the challenges of nearshore monitoring by leveraging satellite observations to complement localized measurements. Further, Wang et al. (2023a) employed multivariable RS datasets derived from satellite observations to assess spatiotemporal variations in cyanoHABs risk levels across eutrophic lakes. Their framework integrated long-term satellite-derived environmental parameters, including precipitation, temperature, and nutrient concentrations, demonstrating the critical role of RS in regional risk assessment and long-term bloom trend analysis. These studies highlight the transformative potential of RS products to enhance monitoring and early warning for bloom events. However, obstacles such as data accessibility issues and variations in regional performance of RS technologies continue to persist. Future efforts should focus on refining the integration of RS with in-situ and aerial systems to enhance prediction accuracy and support adaptive management strategies for cyanoHABs control.

In comparison, monitoring smaller inland water bodies requires a higher spatial resolution, resulting in narrow swath widths and a lower temporal resolution, thus requiring the merging of multiple satellite data products, such as integrating Operational Land Imager with Visible Infrared Imaging Radiometer Suite (VIIRS) and MODIS data (Pahlevan et al., 2014; Stockwell et al., 2020). The choice of technique or satellite product is a trade-off among the spatial, temporal, and spectral resolutions of different satellites and their operation timeframes. Recent launches of Sentinel-2 and Sentinel-3 carrying Multi-Spectral Instrument (MSI) and Ocean and Land Color Instrument (OLCI) sensors have offered opportunities for the science community to advance improved methodologies for monitoring cyanoHABs and other in-water applications (Ansper and Alikas, 2019; Cazzaniga et al., 2019; Gernez et al., 2017). However, the implication of these choices concerning cyanoHABs analysis in smaller water bodies is an emerging field requiring further research.

Substantial research efforts have been directed towards monitoring cyanoHABs across fresh and coastal waters, with a primary focus on the specific spectral range of cyanoHAB proxies, including Chla and PC (Matthews and Bernard, 2013; G. Wang et al., 2016; Liu et al., 2022a). In general, two main bio-optical algorithms have been used: empirical methods that determine cyanoHABs biomass from top-of-atmosphere or Rayleigh-corrected reflectance and semi-empirical methods that directly assess cyanoHABs biomass from water-leaving (aquatic) reflectance after conducting atmospheric correction (AC) effects (Matthews and Bernard, 2013; Odermatt et al., 2018). The performance of these algorithms is limited to the specific optical water types they have been developed for. Further, due to the diversity in optical water types (Spyrakos et al., 2018), different semi-empirical algorithms are used to address cyanoHABs characterization (Buma and Lee, 2020).

Converting satellite imagery of cyanoHABs into consistent information for use in environmental management frameworks is a challenging task (Anttila et al., 2018; Torok et al., 2019). However, the future of EO-based cyanoHAB monitoring appears promising, bolstered by recent advancements in technology that yield greater data availability, variability, and accuracy, along with new satellite missions (Torok et al., 2019; Ustin and Middleton, 2021). Consequently, the distribution of satellite-derived cyanoHABs products to a diverse range of stakeholders is critical. It can enhance cyanoHABs management strategies and establish effective early warning systems for blooms in freshwater environments. The key challenge lies in fully integrating EO-based cyanoHABs data streams into services that researchers, monitoring agencies, policy developers, and end-users within the aquatic resource community can fully

utilize and apply.

A variety of cyanoHABs monitoring and early warning services and tools leveraging Earth observation products are currently in use. Notable among these are the Environmental Protection Agency CyAN project (Schaeffer et al., 2018), the Baltic Sea cyanobacteria bloom monitoring and assessment using the Cyanobacterial Bloom Index (CyaBI) (Anttila et al., 2018), the CyanoTRACKER project (Mishra et al., 2020), EOLakeWatch by ECCC (Environment and Climate Change Canada) (Binding et al., 2021), AlgaeMAP (Algae Bloom Monitoring Application) (Lobo et al., 2021), and the interactive cloud-based dashboard namely "CyanoKhoj" in GEE (Maniyar et al., 2022).

Successful implementation of these services and tools has been instrumental in streamlining the efforts of water resource management agencies to respond to cyanoHABs, enhancing their decision-making processes (Binding et al., 2021; Schaeffer et al., 2018). Far from replacing traditional in situ sampling programs, Earth observation products, and field data work hand-in-hand, providing complementary methods for more comprehensive and accurate water quality assessments. The challenge and interest lie in distilling the vast amounts of complex cyanoHABs monitoring data into practical, replicable, readily analyzable, and user-friendly platforms.

3. Methodology

For this evaluation, we chose five widely-used cyanoHABs monitoring systems—CyAN, CyaBI, CyanoTRACKER, EOLakeWatch, and CyanoKhoj—due to their proven effectiveness through documentation and diverse approaches to harmful algal bloom (cyanoHABs) monitoring in freshwater and inland waters. These systems represent a range of remote sensing methodologies and scales of application, providing early warnings and actionable insights for managing water quality, ecosystem health, and public safety. We select the information involving a thorough review of peer-reviewed publications, ensuring all relevant systems are considered. This comprehensive approach instills confidence in the research and its findings.

This study covers 2016 to 2023, focusing on operational systems that provide public information and warnings for HABs using satellite data. We prioritize high-quality, peer-reviewed studies from Q1 or Q2 journals, except for critical studies before 2016 and relevant legal documents or reports. For example, although CyanoLakes is an early and innovative application using MERIS satellite data for public warnings on cyanobacteria blooms, we excluded it from the primary evaluation since the MERIS satellite is no longer operational. CyanoLakes is instead referenced in the background section as an earlier system from the MERIS era.

We use keywords such as "harmful algal blooms," "cyanobacteria monitoring," "satellite remote sensing," "freshwater monitoring," and "inland water quality" to identify relevant studies, narrowing the scope to systems that operate at the freshwater/inland water level.

4. Satellite-derived cyanoHABs detection applications and their characteristics

From the foundational backdrop of integrating Earth observation with in situ monitoring, we segue into a detailed exploration of satellite technologies to detect cyanoHABs. This section delves into the operational services that leverage advanced Earth observation sensors, including MSI on Sentinel-2, the Ocean and Land Colour Imager (OLCI) on Sentinel-3, and the historical data from the MEdium Resolution Imaging Spectrometer (MERIS) which, while no longer in operation, provides invaluable records from 2003 to 2011. The intricacies and implications of these satellite-based services are detailed in Table 1 and Appendix A Table A1, which present a comprehensive overview of their characteristics and utility in cyanoHABs monitoring. This review covers operational services up to 2023, offering insights into their limitations, benefits, and current status. The currently operational services include CyAN and CyanoTRACKER, while CyaBI, EOLakeWatch, AlgaeMAP, and Cyano Khoj are no longer operational.

4.1. CyAN (Cyanobacteria Assessment Network) (2002–2012 and 2016–present)

The CyAN (Cyanobacteria Assessment Network) application (Fig. 1b) utilizes satellite data from OLCI (Level-1B) (see Appendix A Table A1) (Schaeffer et al., 2018). The CyAN project is a joint initiative involving multiple agencies, including the Environmental Protection Agency (EPA), the National Aeronautics and Space Administration (NASA), the National Oceanic and Atmospheric Administration (NOAA), and the United States Geological Survey (USGS) (Schaeffer et al., 2018). CyAN aims to establish a timely early warning indicator system for detecting algal blooms in the U.S. to evaluate water quality and protect the safety of aquatic ecosystems and human health (Clark et al., 2017) (Table 1). The core processing system of the CyAN application is the SeaWiFS Data Analysis System (SeaDAS) software package, which is used to derive abundance information for Cyanobacterial harmful algae blooms (CyanoHABs) (Baith et al., 2001). SeaDAS is a comprehensive and user-friendly software package provided by the SeaWiFS project for processing, displaying, analyzing, and quality-checking a wide range of satellite products. Here, we elaborate on the methodology for this service as follows (see Appendix A for Eq. (A.11) to (A.17)).

1. The pre-processing step is dedicated to obtaining coefficients for Rayleigh correction (Gordon, 1997; Schaeffer et al., 2018). Spectral albedo $\rho_{rc}(\lambda)$ is generated by eliminating molecular absorption and Rayleigh scattering from the top-of-atmosphere signal. The Rayleigh-corrected OLCI dataset has a 620 nm band that assists in differentiating among cyanobacteria and other algae groups.
2. Clouds are masked to eliminate pixel misidentification caused by intense algal blooms, which can lead to high reflectance.
3. The estimated $\rho_{rc}(\lambda)$ is used in the calculation of the CI from the spectral shape (SS) (Appendix A) algorithm centered at 681 nm (CI = -SS (681)) (Wynne et al., 2008).

Table 1
cyanoHABs services Characteristics.

Operational System	Agency	Algorithm	Product/output	Operational service	Satellite	Spatial(m)/ Temporal resolution	Geographic coverage	Time/duration of the operation	Ref
(CyAN)	The U.S. Environmental Protection Agency (EPA)	CI = -SS (681)) cyanoHABs abundance = CI (cyano) $\times 10^{-8}$	Cyanobacteria Index (CI) cyanoHABs abundance	Copernicus Sentinel-3 Open Access Hub daily (https://oceansci.gsfc.nasa.gov/)	Sentinel-3A and Sentinel-3B- Standard OLCI Level-1B data MERIS (2002–2012)	Sentinel-3 satellite (OLCI): 300 m at nadir/global coverage every 4 days MERIS: 300m global coverage every 3 days	USA	MERIS (2002–2012) and OLCI on Sentinel-3A, (2016-present) and OLCI on Sentinel-3B, (2018-present).	(Wynne et al., 2008, 2010)
(CYaBI)	Finnish Environment Institute (SYKE)	Empirical cumulative distribution function to calculate indicative variables. CyaBI index by averaging the normalized time series from each indicative variable	Cyanobacterial Bloom Indicator (CyaBI)/ blooms characteristics (duration, volume, and severity) for each sub-basin/The current cyanobacterial bloom situation (an average condition of recent 5 years) and comparing it to the estimated target level for 'good environmental status' (GES)	MERIS: EOLI-SA service by ESA (https://earth.esa.int/web/guest/eoli) MODIS: NASA's Ocean colour near real-time data service (http://oceancolor.gsfc.nasa.gov/)	Sentinel-3A and Sentinel-3B- Standard OLCI Level-1B data. MERIS (2002–2012)	Sentinel-3 satellite (OLCI): 300 m at nadir/global coverage every 4 days. MERIS: 300m global coverage every 3 days	Baltic Sea: The Gulf of Finland & Northern Baltic Proper & Western Gotland Basin & Eastern Gotland Basin	2006–2008 and 2011–2015	(Gentle, 2009) And (Anttila et al., 2018)
(EOLakeWatch)	Environment and Climate Change Canada (ECCC)	Maximum Chlorophyll Index (MCI) method	Maximum Chlorophyll Index (MCI)	Copernicus Sentinel-3 Open Access Hub daily (https://oceansci.gsfc.nasa.gov/)	Sentinel-3A OLCI Level-1 FR MERIS (2002–2011) Level-1 FR	MODIS: 1000 m entire Earth's surface every 1–2 days MERIS: 300m global coverage every 3 days	Canadian lakes (Lake Winnipeg (LW); Lake Erie (LE); Lake of the Woods (LoW))	MERIS (2002–2011) and OLCI (2015–2021 present)	Gower et al. (2008)
(CyanoTRACKER)	National Science Foundation (NSF) and Georgia Water Resources Institute	Chl-a concentration was derived from CyanoSense Rrs (remote sensing reflectance data) using the normalized difference chlorophyll index (NDCI) model.CCD:	cyanobacteria cell density (CCD)	Copernicus Sentinel-2 Open Access Hub	Sentinel-2 MSI level 1-C (L1-C)	Sentinel-2 MSI is dependent on the particular spectral band (10m, 20m, 60m) with spatial coverage (land and coastal areas between latitudes 56°S and 83°N)/The revisit frequency of each single SENTINEL-2 satellite is 10 days and the combined constellation revisit is 5 days.	Waterbodies in southeastern U.S (Lake Oconee, Lake Chapman, and Lake Oglethorpe in GA)	January 2011 to August 2016 (category-wise seasonal trends in tweets corresponding to CyanoHABs events were analyzed for 20 months in 2015–2016 labeled data)	(Mishra and Mishra, 2012; Page et al., 2018).
(AlgaeMap)	Brasil (CAPES)	Chl-a concentration was derived from NDCI based on a	Chl-a concentration, and Trophic State Index (TSI)/The output	Copernicus Sentinel-2	Sentinel-2 MSI, level 1-C (L1-C)	30m and temporal resolution: 5 days	Tiete River Bain, located in the State of Sao Paulo, Brazil	August 2015 until February 2021	(Lobo et al., 2021;

(continued on next page)

Table 1 (continued)

Operational System	Agency	Algorithm	Product/output	Operational service	Satellite	Spatial(m)/ Temporal resolution	Geographic coverage	Time/duration of the operation	Ref
		non-linear fitting model, which is then used to determine the Trophic State Index (TSI) through a tree-decision model.	is a binary classification that helps to detect the HAB, where NDCI is classified either as non-bloom (Oligo, Meso, and Eutrophic levels) or HAB condition (Super and Hypereutrophic levels)	Open Access Hub					Carder and Steward, 1985)
(CyanoKhoj)	National Science Foundation (NSF)	CI = -SS (681)), cyanoHABs abundance = CI (cyano) $\times 10^8$ Chl-a concentration was derived from NDCI by merging earlier established models based on JavaScript code in GEE platform.	Cyanobacteria Index (CI) and cyanoHABs abundance/spatiotemporal maps of Chlorophyll-a (Chl-a) content and cyanoHABs	Copernicus Sentinel-3 Open Access Hub daily	Sentinel-3, OLCI data level-1 (OL_1_EFR)	Sentinel-3 satellite (OLCI): 300 m at nadir/global coverage every 4 days	Lakes and reservoirs geographically spread across five states in India: Bargi and Gandhisagar Dams in Madhya Pradesh, Hirakud Reservoir in Odisha, Ukai Dam in Gujarat, Linganamakki Reservoir in Karnataka, and Pulicat Lake in Tamil Nadu	September to November 2018	Wynne et al. (2008) And (Wynne et al., 2010)

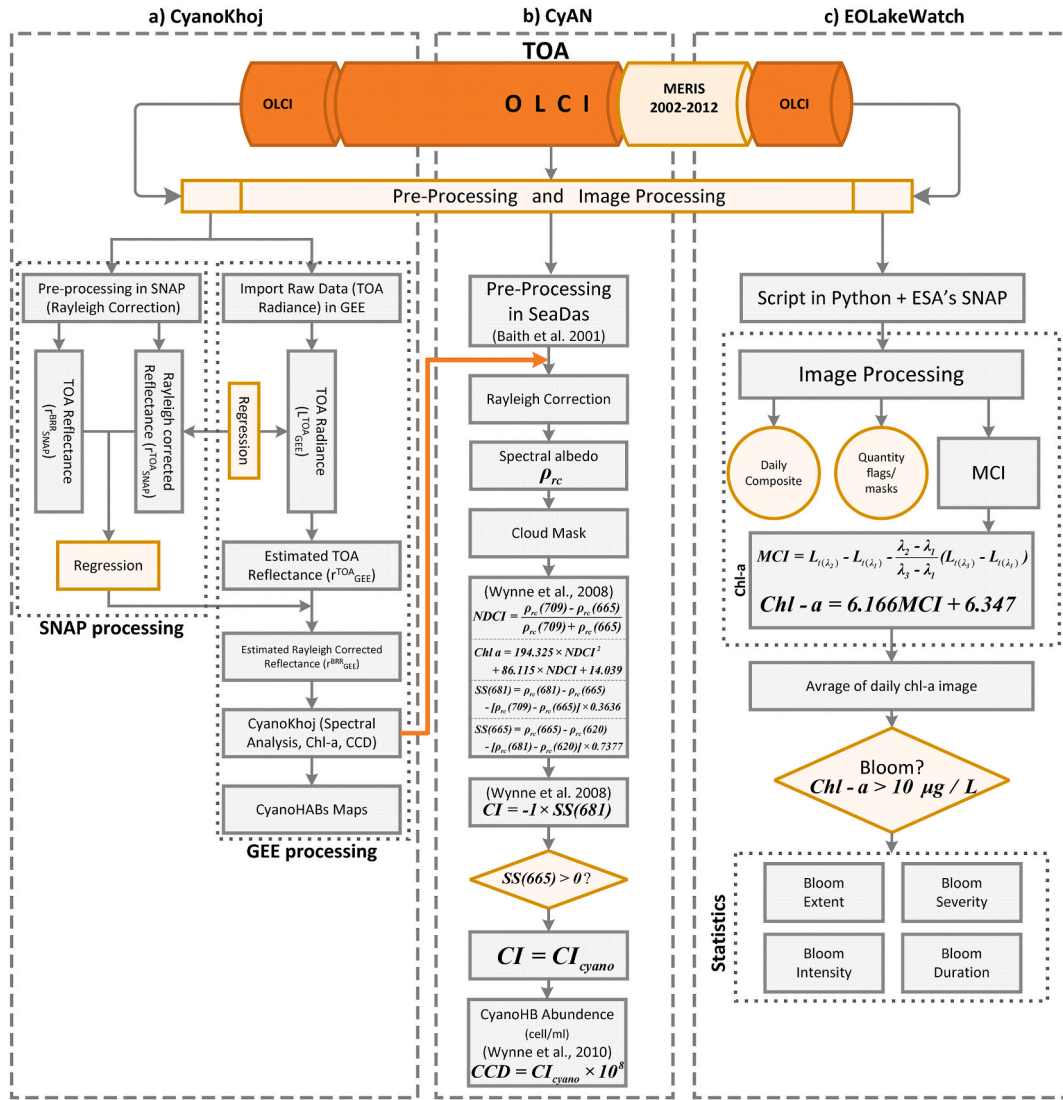


Fig. 1. Flowchart of overall methodology in cyanoHABs services, including pre-and image processing, to drive the cyanoHABs products. a) CyanoKhoj, b) CyAN, c) EOLakeWatch.

4. If $SS(665) > 0$ then $CI = CI_{cyano}$, and the CI is converted into CyanoHABs abundance (cells/mL) via *CyanoHAB abundance* = $CI_{cyano} \times 10^8$ (Wynne et al., 2010).
5. Weekly 7-day composite images are generated by retaining the maximum value detected for each pixel during the week. These weekly composites enable managers to combine timely data distribution with the most available data, even in the presence of factors such as cloud cover interference.

According to Lunetta et al. (2015) and Clark et al. (2017), the CI algorithm exhibited a correspondence of over 80% (corresponding to “Low” cell count range) with in situ samples collected within ± 7 days of a satellite matchup. Lunetta et al. (2015) demonstrated that based on CI validation results, MERIS showed a robust estimation for satellite-derived values below 109,000 cells/mL and above 1,000,000 cells/mL (mean absolute percentage error, MAPE = 28.6%, coefficient of determination, $R^2 = 0.95$), while lower correspondence performance of CI algorithm was reported for the range between 109,000 and 1,000,000 cells/mL. However, the poorer correspondence within this concentration range (i.e., between 109,000 cells/mL and 1,000,000 cells/mL) was expected because it was influenced by insufficient validation, meaning there were limited in situ observations to validate the satellite estimates, and the sizeable temporal period for coincident satellite matchups (Lunetta et al., 2015).

The CyAN app was developed and validated using Agile methodology (Schaeffer et al., 2018). User requirements for the app were initially gathered through interviews with water quality managers. These requirements were identified by Schaeffer et al. (2013) and served as the starting point for the app’s conceptualization and design. The app was developed using a series of code development

challenges, focusing on user feedback and continuous improvement, including Jira, Confluence project management software, and a Git software repository (Schaeffer et al., 2018). The app meets National Institute of Standards and Technology (NIST) security standards and has been beta-tested since 2017 with users in various federal and state agencies. The app's functionality and satellite data were validated against 25 U.S. states' health advisories, revealing that in some cases, the app detected toxic blooms one week earlier than routine monitoring. According to Schaeffer et al. (2018), of the 25 events, 16 (64%) would have been identified at least one week earlier with the app and RS data. A case study in Utah.

Lake showed that the CyAN app could assist water quality managers in detecting toxic blooms or taste and odor issues by targeting specific locations within lakes at specific times (Stroming et al., 2020).

4.2. CyaBI (cyanobacterial bloom indicator) (2006–2008 and 2011–2015)

CyaBI (Cyanobacterial Bloom Indicator) (Fig. 3) uses the satellite-derived Chla concentrations and water turbidity from the MERIS and MODIS daily algal bloom product of the Finnish Environment Institute (SYKE) to evaluate the ecological status by integrating information on cyanobacterial blooms into the CyaBI index (see Appendix A Table A1) (Anttila et al., 2018) (Table 1).

The CyaBI index was particularly viable for the Gulf of Finland because the RS-based data set, namely Fraction with Cyanobacterial Accumulations (Kahru and Elmgren, 2014) values from 1979 to 1996 demonstrated good compatibility with 'good environmental status' (GES), together with negligible variability in the cyanobacterial bloom condition. However, this novel cyanobacterial bloom indicator was tested in four Baltic Sea sub-basins, including the Gulf of Finland, Northern Baltic Proper, Western Gotland Basin, and Eastern Gotland Basin. The first step of the procedure for deriving the algal bloom product involves classifying remote sensing (RS) estimates of Chla and turbidity into four classes based on empirical concentration values.

- [0]: No algal surface accumulations
- [1]: Potential algal surface accumulations
- [2]: Likely algal surface accumulations
- [3]: Evident algal surface accumulations

The two classifications are combined using each pixel's highest surface accumulation class to create the algal bloom product. The procedures to assess the ecological status of cyanobacterial blooms include the following steps (Anttila et al., 2018).

1. Aggregating RS observations: the algal bloom products are spatially aggregated to calculate an "algae barometer" value for each sub-basin during the study period (Rapala et al., 2012). The AB value is a weighted sum of the proportion of positive algal bloom estimations in the potential, likely, and evident algal surface accumulations categories (Rapala et al., 2012).
2. Indicative variables for the CyaBI index: algal bloom duration, volume, and severity are considered indicative variables and computed for each sub-basin and year using an empirical cumulative distribution function (Gentle, 2009).
3. Estimating ecosystem status: the indicative bloom event variables are merged into the CyaBI index by averaging the normalized time series from each variable.
4. Setting target levels for Good Ecological Status (GES): the target level for GES is set using a RS-based data set named FCA, covering the years 1979–2014. In each sub-basin, the FCA GES level is converted into the respective CyaBI values based on a linear model among the two data sets from the four sub-basins and during 2003–2014. Consequently, the CyaBI index indicates a significant linear correlation with the FCA ratio among the combined data set.

According to Attila et al. (2013), the method was studied in four selected sub-basins of the Gulf of Finland from 2003 to 2015 (Table 1). The Chla concentrations were estimated from RS data using the Basic ERS & ENVISAT (A) ATSR and MERIS Toolbox (BEAM) plug-in processor MERIS from 2003 to 2011, through the Case-2 Water Properties Processor (FUB) method as described by Schroeder et al. (2007). Turbidity estimation from the MERIS data was carried out for the same period using the BEAM plug-in processor Case 2 Regional (C2R; version 1.6.2), as reported by Doerffer and Schiller (2010). The Chla and turbidity values for MODIS data (from 2012 to 2015) were obtained using the algorithms developed by Maritorena et al. (2002, 2010) and O'Reilly, (1998, 2000), with an average temporal coverage of 49% and average spatial coverage ranging from 18 to 31%. These algorithms were optimized for performance by comparing them to available in situ monitoring program observations. The algal bloom product was validated against the regular surface algal observations with a good correspondence value in 77% of cases. The accuracy assessments of SYKE's MERIS Chla products and SYKE's MODIS Chla products against *in-situ* data sources had a determination coefficient value (R^2) ranging from 0.47 to 0.64 and 0.82, respectively (Alasalmi et al., 2013; Attila et al., 2013). Note that according to Seegers et al. (2018), commonly used statistical metrics, such as R^2 , for assessing the performance of ocean color studies may not be suitable for non-Gaussian distributions and outliers. Metrics like bias and mean absolute error are more robust for this purpose. It is essential to consider the limitations of R^2 and use appropriate metrics to evaluate algorithm performance for ocean color satellite data. Similar accuracy assessments for SYKE's MERIS-based water turbidity product and SYKE's MODIS-based turbidity product resulted in R^2 ranging from 0.76 to 0.83 (RMSEs of 0.73–0.86 FNUs) and (0.49 RMSE 0.56 FNU), respectively (Attila et al., 2013; Simis et al., 2013). Cloudiness was found to be the main factor impacting spatial and temporal resolution. The CyaBI index showed improved stability in the Eastern Gotland Basin, Western Gotland Basin, and the Gulf of Finland between 2009 and 2015 but worsened in the Northern Baltic Proper (Anttila et al., 2018).

4.3. CyanoTRACKER (2015-present)

The CyanoTRACKER framework, developed by the University of Georgia (UGA) (Fig. 2a), collects and integrates the combined community reports at location measurements using CyanoSense, remote-sensing data using Sentinel-2 level 1 (see Appendix A Table A1), and digital image analysis to implement in initial detection and continuous monitoring of spatio-temporal growth of CyanoHABs (Mishra et al., 2020).

According to the original paper, the various components of CyanoTracker, such as social media, data mining, and sensor cloud, were fully operational from 2015 to 2018. However, only the social media aspect of CyanoTracker is currently operational, and it is being used to share news and reports related to CyanoHABs.

This service has three major components: 1) community report, 2) CyanoSense measurements at the site, 3) satellite remote sensing (Table 1).

Initially, the CyanoHABs affected water bodies are identified using online social media reports and cloud computing platforms, and twitter are the primary source of social cloud data. The validity of social media reports is verified by CyanoSense measurements, which collect close-range hyperspectral reflectance measurements and analyze the characteristic 620 nm absorption feature. CyanoSense was developed as a part of CyanoTracker and operated remotely through the cell phone network for in situ optical measurements. Once CyanoHABs are verified, their spatial-temporal evolution is modeled and mapped using satellite data. To learn more about the

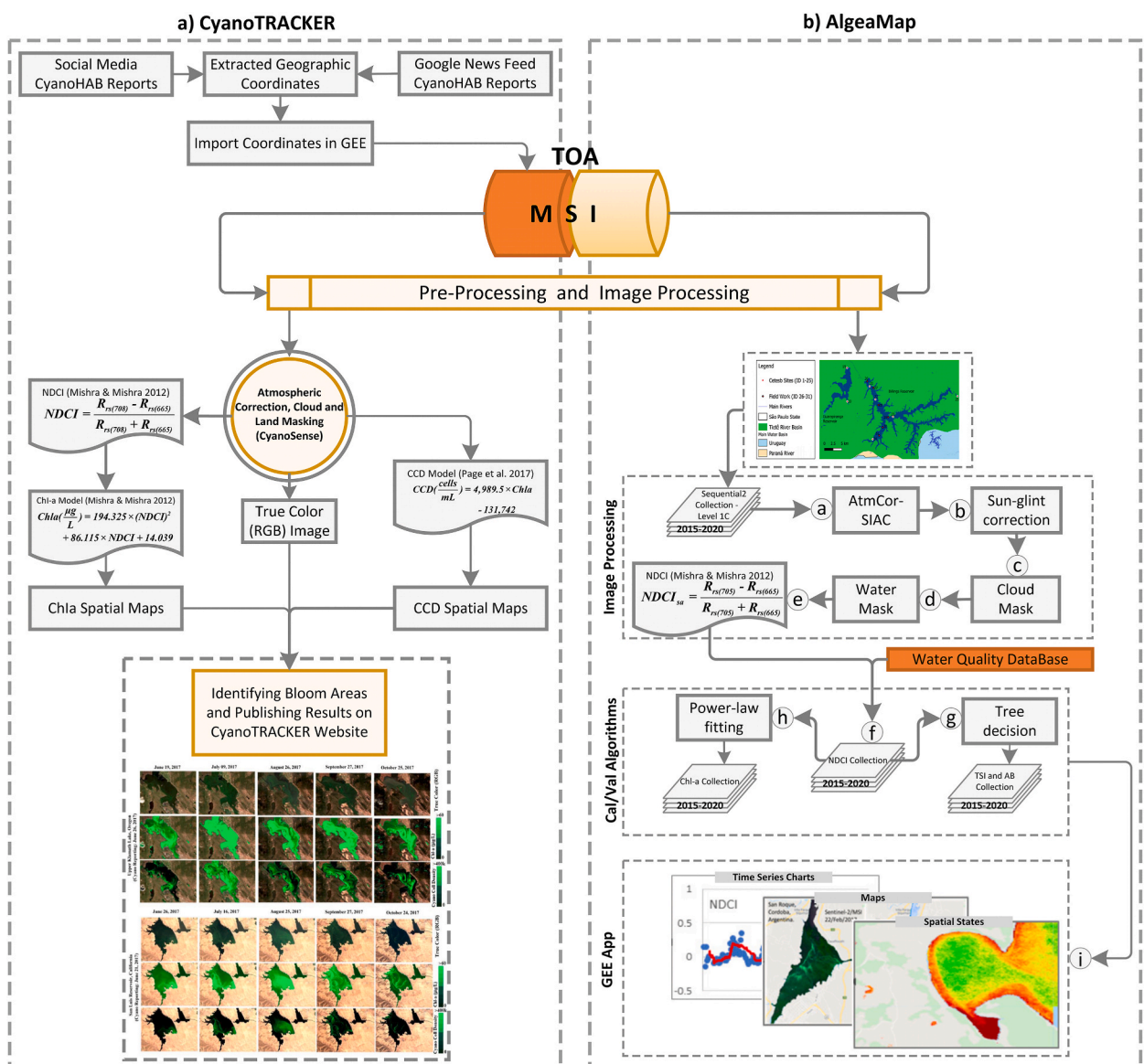


Fig. 2. Flowchart of the overall methodology in cyanoHABs services, including a) CyanoTRACKER, b) AlgaeMap, that utilize S2/MSI imagery.

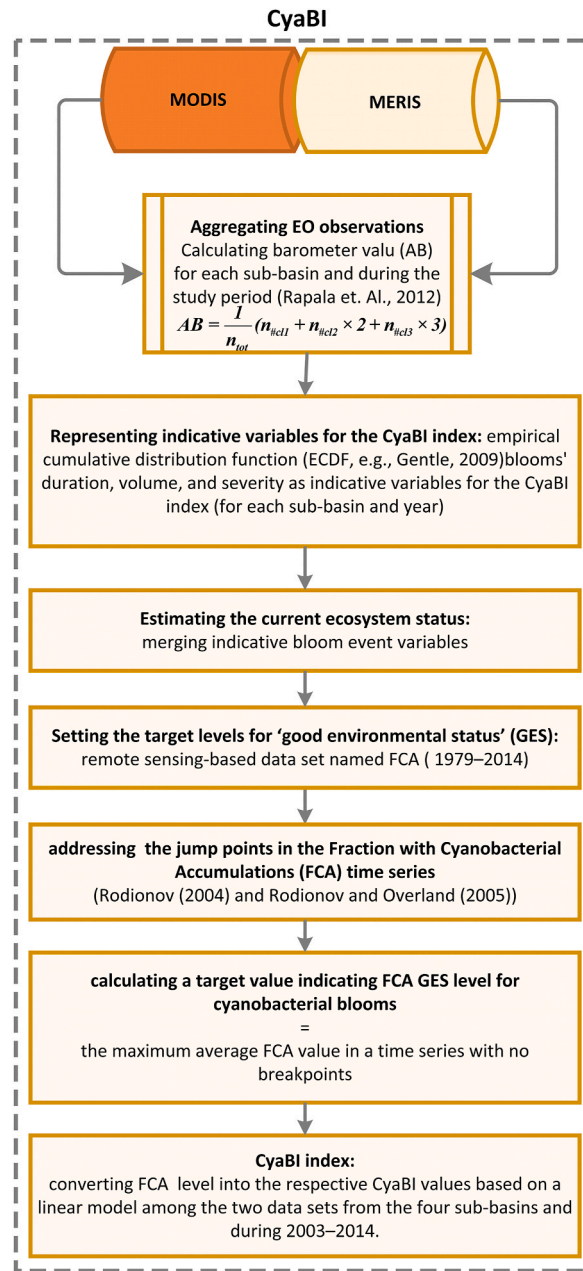


Fig. 3. Flowchart of the applied procedure in CyaBI.

methodology used for this service, refer to [Appendix A](#) (for Eqs. (A1) to (A8)) for detailed information.

In the final stage, the location of CyanoHABs sites obtained via the social cloud and validated by CyanoSense measurements is imported into the GEE ([Weber, 2017](#)) for satellite-based detection and spatio-temporal mapping. The CyanoSense sensors were deployed at select sites on a rotational basis, and a field crew regularly maintained the system.

The specific locations for recorded CyanoHABs sites are uploaded onto a GEE ([Weber, 2017](#)). After that, Sentinel-2 level 1 imagery closest to the reported date is also imported to GEE for bio-optical modeling. This process is commonly known as "matchup" identification, as it involves identifying the closest match between available satellite data and the reported date. Before implementing the bio-optical models, pre-processing steps such as land, cloud, and glint masking are performed on each Sentinel-2 dataset. Further, AC via modified atmospheric correction for inland waters (MAIN) method developed by [Page et al. \(2019\)](#) is used on each data. Bio-optical models for Chla ([Mishra and Mishra, 2012](#)) (Eq. (4)) and cyanobacteria cell density (CCD) ([Page et al., 2018](#), Eq. (6)) are performed to quantify the spatio-temporal variation of CyanoHABs at all recorded areas. The CCD algorithm by [Page et al. \(2018\)](#) uses two cyanobacteria species, *Aphanizomenon* and *Dolichospermum* as dominant cyanobacteria species for 2016 Utah Lake Bloom ([11](https://deq.</p>
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utah.gov/water-quality/utah-lake-jordan-river-canals-algal-bloom-2016). Based on the CyanoTRACKER site reports, the dominant cyanobacteria species in the sites contain *Microcystis*. Thus, CCD results can present a relative PC estimate without a site-specific model calibration (Mishra and Mishra, 2012; Page et al., 2018):

$$CCD \left(\frac{\text{cells}}{\text{mL}} \right) = 4989.5 \times \text{Chla} - 131742 \quad (1)$$

Further, selecting the time-series analysis period depends on location-specific image availability. Ultimately, the spatio-temporal pattern of CyanoHABs at recorded areas is analyzed with time-series maps derived from previous satellite data. Social media reported more than 130 locations with potential CyanoHABs occurring from June 2017 to August 2017 in the United States. On each date, the GEE-based CCD maps followed the bloom patterns, and time-series analysis of RS data showed the start, peak growth, and disappearance of the bloom in each water body.

The original paper's authors reported developing a cheaper and improved dual-headed sensor system named Cyanosense 2.0. This system will be tested for detecting cyanobacterial blooms from May to October 2023 and is expected to improve detection accuracy.

4.4. EOLakeWatch (2002–2011 and 2015–2021)

Algal bloom products are derived from the OLCI (Level-1 FR) and its predecessor, the MERIS (Level-1 FR), onboard ESA's Envisat (2002–2011) (see Appendix A Table A1). In June 2020, EOLakeWatch (Fig. 1c) was launched by the Environment and Climate Change Canada (ECCC) to deliver a suite of EO-derived algal bloom products to support inland water cyanoHABs monitoring (Binding et al., 2021). EOLakeWatch builds on the previous work of ECCC that enhances and validates algorithms for RS-based algal bloom monitoring (Binding et al., 2011; 2013, 2018, 2019) (Table 1).

Further, the methodology workflow for this service contains the following.

1. Top-of-atmosphere spectral radiance is georeferenced and is calibrated to geophysical units ($\text{W}/\text{m}^2/\text{sr}/\mu\text{m}$), which are subsets to specific regions of interest for each water body.
2. Images are masked according to quality flags (sun glint, duplicate pixels, bright, coastline, or otherwise invalid pixels).
3. Estimating Maximum Chlorophyll Index (MCI): Chla retrieval algorithms exploiting the red and NIR bands (red-NIR) portion of the spectrum perform well in turbid eutrophic waters, and line-height algorithms, such as the MCI, are particularly favorable. The MCI quantifies a peak in top-of-atmosphere radiance at 708 nm relative to a baseline interpolated between bands on either side, capturing the red-edge reflectance feature associated with dense surface algal blooms.
4. MCI slope is used to mask extreme sediment events, which have led to potential false positive bloom detection in red-NIR line-height-based algorithms (Zeng and Binding, 2019).

To test this service, three large turbid, eutrophic Canadian lakes (Lake Winnipeg, Lake of the Woods, and Lake Erie) were monitored by ECCC from June to October between 2002 and 2019 (Binding et al., 2021).

The downloaded products were (a) OLCI Level-1 FR imagery on a daily basis from June 1 to October 31 and (b) MERIS Level-1 FR (300 m spatial resolution) imagery.

Daily Chla images were generated and combined into rolling 14-day composite images. When Chla exceeding of $10 \mu\text{g}/\text{L}$, the algal bloom flag was raised on a pixel-by-pixel basis. This threshold follows the WHO (World Health Organization) guideline levels for relatively mild/low probabilities of adverse health impacts of $10 \mu\text{g}/\text{L}$ of Chla when cyanobacteria are dominant.

This validation assessment showed an average peak bloom intensity (the average Chla within the area flagged as in bloom) of $30.7 \mu\text{g}/\text{L}$, $42.8 \mu\text{g}/\text{L}$, and $53.5 \mu\text{g}/\text{L}$ at Lake of the Woods, Lake Winnipeg, and Lake Erie, respectively. There was seasonal and inter-annual variability in bloom intensity on all three lakes. A significant variance was observed among the derived bloom indices, meaning the most extensive bloom was not necessarily the most extended or intensive one (Binding et al., 2021).

4.5. AlgaeMAP (Algae Bloom Monitoring Application) (August 2015 until February 2021)

AlgaeMAP (Fig. 2b) was built within the GEE environment using Sentinel-2 imagery (level 1) to provide water quality parameters at high spatial (30 m) and temporal (~ five days) resolution (Lobo et al., 2021) (Table 1). See Appendix A (Eqs. (A9) and (A10)) for detailed information.

For a new service involves three steps (Lobo et al., 2021).

1. Developing a code in GEE to process Sentinel-2 imagery for atmospheric effects, cloud, and water mask, and generate the Normalized Difference Chlorophyll-a Index (NDCI). The NDCI is used to estimate Chla concentration based on a non-linear fitting model, which is then used to determine the Trophic State Index (TSI) (Carder and Steward, 1985) through a decision-tree model. The TSI decision-tree categorizes every pixel into five levels of the TSI (Oligo, Meso, Eutrophic, Super, and Hypereutrophic). Further, in combination with Chla concentration, TSI can be ranked into six classes, ranging from Ultra-oligotrophic to Hyper-eutrophic.
2. Collecting quality data to validate the index. Project participants must provide in situ data to validate the NDCI or other Chla algorithms. Note that NDCI image collection (resampled to 30 m) can be retrieved and utilized directly on the GEE platform. To

generate NDCI, the deployed Sentinel-2 images are initially corrected for atmospheric and sun-glint effects using SIAC (Satellite Invariant Atmospheric Correction) and subtracting the B12 (2190 nm) from Bands 2–11, respectively (Yin et al., 2019). The data is then classified into estimated TSI levels and compared to the NDCI derived from the imagery. A paired *t*-test (*p*-value = 0.05) is applied to determine the NDCI distribution for each TSI category between all TSI classes. A decision tree based on the Monte Carlo model determines the NDCI threshold that is categorized into five TSI levels. The output is a binary classification that helps to detect the cyanoHABs, where NDCI is classified either as non-bloom (Oligo, Meso, and Eutrophic levels) or cyanoHABs condition (Super and Hypereutrophic levels).

3. Building a script into a GEE application that any end-user can access to visualize location and date, select a map, and create time-series charts and spatial stats maps. All data, layers, and charts are downloadable.

This tool was first tested in the Tiete River Basin, Brazil, from August 2015 to February 2021 (Lobo et al., 2021). In November 2020, in the Billings Reservoir, collected in situ radiometric data were used to evaluate the applied atmospheric and sun-glint corrections of MSI images obtained from SIAC. The Monte Carlo model was applied to derive the Chla algorithm, which showed a MAPE close to 90%. The algorithm can accurately estimate medium to high Chla concentrations between 10 and 70 µg/L but may have lower accuracy for values below 5 µg/L and above 70 µg/L (Lobo et al., 2021). Algae bloom conditions were considered for levels of hyper-eutrophic, while non-bloom conditions were considered Oligo, Meso, and Eutrophic levels (Lobo et al., 2021).

4.6. Cyano Khoj (September to November 2018)

CyanoKhoj (Fig. 1a) is a cloud-based dashboard in GEE (CyanoKhoj, 2021) that retrieves Chla concentration and CI from Sentinel-3 data (Table 1). It calculates these values using processed Level-1 OLCI data, which has been analyzed via the Sentinel Application Platform and GEE. In comparison, the procedure for retrieving CI and Chla in the CYAN app is utilized through SeaDAS from satellite data (OLCI Level-1B). For the first time, Maniyar et al. (2022) introduced "CyanoKhoj" on GEE for a comprehensive country-wide analysis of CyanoHABs in India, aiming to enhance rapid monitoring and address widespread concerns. This initiative aligns with the methodologies of the Cyan app, which facilitates community-based monitoring in North America through a mobile platform, underscoring CyanoKhoj's capability and applicability beyond India. The procedure in CyanoKhoj involves the following steps (see Appendix A for Eqs. (A11) to (A17)):

1. Pre-processing: OLCI data is processed using the Sentinel Application Platform tool (Fig. 1 and Table 1).
2. Reflectance Correction: The lack of crucial metadata in GEE's OLCI data products creates difficulties for independent pre-processing. However, using Sentinel Application Platform software enables the application of reflectance correction for these data. Hence, a regression model connected to Sentinel Application Platform data estimates the reflectance correction for GEE processing (Fig. 1, steps 1–10).
3. Index value (NDCI, CI) and concentration (Chla, CCD) estimation: The estimation methodology is similar to the CYAN project.
4. Visualization: The analysis results are visualized on the CyanoKhoj dashboard using maps and charts. The results can be used to monitor and track the presence of cyanobacteria in water bodies.

However, CyanoHABs maps are the outcome of the CyanoKhoj dashboard. Like NOAA for routine CCD mapping, CyanoKhoj adopts, Lunetta et al. (2015), CCD model (Eq. (A17), see Appendix A), which builds on the Wynne et al. (2008) model (Eq. (A13), see Appendix A) by minimizing the false positives influenced by other types of algae blooms. Besides, in CyanoKhoj, the Mishra and Mishra (2012) NDCI model has been used to determine the difference between other algal blooms and CyanoHABs. In addition, CyanoKhoj facilitates analysis in terms of all the variables, such as NDCI, CI, Chl-a, and CCD. Clicking on any satellite image pixel produces a spectrum of the ρ_{rc} across the wavelengths of the 21 bands of OLCI. These spectra can be analyzed to indicate an ongoing CyanoHABs, algae bloom, or even cyanobacterial cells in the waterbody at a defined location connected to the clicked pixel.

Maniyar et al. (2022) indicated the benefits of CyanoKhoj by selecting case studies of lakes and reservoirs geographically distributed across five states: Bargi and Gandhisagar Dams in Madhya Pradesh, Hirakud Reservoir in Odisha, Ukai Dam in Gujarat, Langanamakki Reservoir in Karnataka, and Pulicat Lake in Tamil Nadu. They considered September to November 2018 as the time window of their study using CyanoKhoj, which was an appropriate timeframe for near-real-time monitoring and country-wide assessment of CyanoHABs. Using CyanoKhoj, they presented spatiotemporal maps of Chla content and CCD, resulting in a study of the local distribution of the CyanoHABs and their phenology in these water bodies. They provided the first-ever all-India CCD map for 2018, focusing on the spatial spread of CyanoHABs across the country (32 large water bodies across India with severe bloom: CCD > 2, 500,000). The results demonstrated that CyanoHABs were most frequent in nutrient-rich water bodies subjected to industrial and other nutrient-rich discharges. Their temporal evaluation of the blooms indicated the dominance of blooms during the post-monsoon season (September–October) at the peak of nutrient concentrations in the water bodies and a downward trend of blooms towards winter (November–December). The CyanoKhoj's key benefit is its open-source nature that can significantly map CyanoHABs throughout cyanobacteria data-scarce India and apply archived and future Sentinel-3A/B OLCI data on a global level.

4.7. Product uncertainties

Acknowledging the complexities of diverse aquatic ecosystems, it is evident that the variety in trophic levels poses challenges for cyanoHABs monitoring services. Crucially, the accuracy of algal biomass estimations through indices like NDCI, CI, or measurements

such as Chla or CCD is vital for the quality of cyanoHABs service products. However, a potential point of debate centers on the impact of instrument configuration, such as spectral and sensor-specific spatial resolutions, as highlighted in recent reviews on remote sensing for algal bloom monitoring (Rolim et al., 2023). These factors significantly influence the retrieval methodologies, with main uncertainties tied to the precision of algal bloom algorithms, atmospheric correction accuracy, and monitoring instrument specifications.

4.7.1. CyanoHABs services algal bloom retrieval algorithm accuracy

Satellite-based monitoring has revolutionized the detection and management of cyanoHABs, offering tools like CyAN, CyaBI, and others that utilize various indices for accurate assessment. These technologies utilize the distinct optical characteristics of cyanobacteria and Chla to provide critical insights into bloom dynamics. This review delves into the accuracy and application of different algal bloom retrieval algorithms within operational cyanoHABs services, underpinning their role in environmental management strategies.

Among reviewed operational services, CyAN uses CI. The basic theory of CI (Wynne et al., 2008) is that cyanobacteria have much less fluorescence in the 681 nm band compared to Chla. Further, cyanobacteria show stronger backscattering in wavelengths above 700 nm than other phytoplankton groups, such as green algae, diatoms, or dinoflagellates. This is attributed to their smaller cell size, which scatters light more efficiently in this range (Ahn et al., 1992; Matthews et al., 2012). Wynne et al. (2010) and Lunetta et al. (2015) reported a strong relationship between CI and cell counts of cyanobacteria. Further, there is a potential to provide a valid agreement between CI and Chla for a wide range of Chla (16–115 µg/L) (Tomlinson et al. 2016).

In CyAN, the advantage of a seven-day composite is to minimize the influences of cloud cover and to maximize the frequency of useable data to assist management strategies.

To estimate cyanoHAB-related risk levels for issuing warnings or closures, the World Health Organization (WHO) provides a three-tier guideline that specifies concentrations of the ubiquitous photosynthetic pigment Chla and CI (cells/mL). The guideline level of 20,000 cyanobacterial cells per mL (corresponding to 10 µg/L of Chla) proposed by the World Health Organization (Falconer et al., 2005) is, in many cases, adopted. Although RS observations cannot detect toxins (Stumpf et al., 2012), they can quantify CI (Kutser, 2009). Hence, CI is perhaps better suited for risk assessment across broad regions due to limitations related to toxin monitoring (Clark et al., 2017). Notably, threshold setting in the CyAN app allows users to set them based on their preferred CyanoHABs abundance in cells/mL. However, the satellite-derived CI values classification based on appropriate threshold levels is beneficial to minimize the impact on algorithm error and uncertainties.

CyaBI is a useful indicator for evaluating the occurrence and intensity of cyanobacterial blooms in the Baltic Sea region. The CyaBI combines two aspects of algal blooms - the summer cyanobacterial surface accumulation estimated from RS observations and the cyanobacteria biomass derived from *in-situ* observations. In the CyaBI project, for each sub-basin, the jump points in the FCA time series were addressed according to the approach revealed by Rodionov (2004) and Rodionov and Overland (2005). Then the minimum amount of observed algal accumulations (i.e., the maximum average FCA value) in a time series with no breakpoints was considered a target value indicating the FCA GES level for cyanobacterial blooms. After that, the standard error of the FCA value throughout the target period was applied as one uncertainty principle for the target setting. Finally, this provides a comprehensive picture of the current ecosystem status. The CyaBI is limited to ten open-sea sub-basins in the Baltic Sea and is not applicable in specific regions where blooms do not occur.

One of the advantages of the CyaBI is its ability to assess the pelagic habitats in the Baltic Sea, where many cyanobacteria species are dominant in response to eutrophic conditions. Low values of CyaBI indicate high eutrophication levels, providing valuable information for addressing this environmental issue. However, it is crucial to use a combination of indicators tailored to the assessment area for a comprehensive understanding of the local ecosystem. (Magliozzi et al., 2021).

Among the mentioned cyanoHABs monitoring tools, CyanoTRACKER, AlgaeMap, and CyanoKhoj Dashboard use NDCI (Mishra and Mishra, 2012) for Chla estimation derived from remote sensing reflectances (R_{rs}). In phytoplankton-rich waters across the globe, NDCI has been demonstrated to estimate a broad Chla concentration range using, e.g., Sentinel-2 imagery (Watanabe et al., 2017; Caballero., 2020; Rodríguez-Benito., 2020). NDCI is one of several red (~670 nm—high Chla absorption peak)-NIR (705 nm—maximum phytoplankton reflectance sensitivity) indices that have been developed and validated for satellite-based cyanoHABs detection (Johansen et al., 2022). Given the spectral band architecture of NDCI, it clearly overestimates the Chla values in case of the increase in the difference between remote sensing reflectances 708 and 665 (Mishra and Mishra, 2012). Further, any disproportionate increase or decrease in reflectance at 665 and 708 nm causes an inaccurate assessment of Chla. As such, pixels with a disproportionate rise in reflectance at 665 nm compared to 708 nm will create extreme negative values; likewise, a disproportionate increase in reflectance at 708 nm will produce extreme positive values of Chla (Mishra and Mishra, 2012).

MCI is another red-NIR algorithm method similar to NDCI, which has been applied in the EOLakeWatch service. MCI has been well performed in turbid eutrophic waters. Like NDCI, because of using top-of-atmosphere, it is known to be reasonably insensitive to the uncertainties of reflectance linked to the challenges of AC across turbid eutrophic inland waters (Gower et al., 2008; Gilerson et al., 2010). Further, the high DOC and mineral scattering impact is assumed to be negligible.

Nevertheless, this threshold to identify the bloom on a pixel-by-pixel basis for cyanoHABs-related studies is highly variable and impactful on derived bloom statistics. For example, according to Binding et al. (2021), the Lake Erie bloom extent was determined in their study based on agreement with that of Stumpf et al. (2012), which similarly reported the peak bloom extent of 2011 to be over 5000 km² applying the MERIS Cyanobacteria Index (CI). The nominal CI threshold equivalent to 20,000 cells/mL, referenced by Davis et al. (2019), was consistently adopted in Binding et al. (2021), mirroring its application across different studies for bloom identification on a pixel-by-pixel basis. In comparison, Sayers et al. (2019a) highlighted substantially lower Lake Erie algal bloom extent. It can be illustrated by the various thresholds of Chla (concentrations greater than 18 µg/L) they adopted to address the bloom

conditions.

Furthermore, the negative influence of a rolling-average product increases the uncertainty in detecting cyanoHABs extreme events in bloom indices and high-frequency variability, as reported for MCI (Binding et al., 2018; 2021). For instance, the peak bloom extent reported by Binding et al. (2021) provided by EOLakeWatch for Lake Winnipeg was, on average, 18% lower than the one indicated in their previous study (Binding et al., 2018) for the 2002–2011 period. The difference is that in their previous study, only whole-lake cloud-free daily images were analyzed instead of the continuous 14-day rolling averages used in the latest one.

CyanoKhoj reports many visualizations, such as NDCI for Chla and CCD. Since various phytoplankton species synthesize Chla, the CCD method only works for known CyanoHABs events and may create higher errors for low cell count areas. Although this method demonstrates a good first step for inland water bodies' resource management, more CCD data are essential to tune and validate the model to be widely applicable.

In summary, the methodologies employed by cyanoHABs monitoring services, through indices like CI, CyaBI, NDCI, and MCI, play a pivotal role in the detection and assessment of algal blooms. Despite facing challenges such as spectral ambiguities and the need for precise threshold settings, these tools significantly contribute to our understanding and management of cyanoHABs risks. The effectiveness of these algorithms is enhanced by their integration with guidelines and standards, such as those provided by the WHO, and their capacity to inform management decisions across varied aquatic environments. Future advancements and refinements in these technologies promise more accurate and comprehensive monitoring of cyanoHABs, ultimately aiding in protecting aquatic ecosystems and public health.

4.7.2. Atmospheric correction induced surface reflectance quality

In quantifying all near-surface biogeochemical traits (e.g., phytoplankton absorption), AC is a prerequisite (IOCCG, 2010). There are two main AC algorithms: (i) image-based approach (two-step); and (ii) atmospheric radiative transfer codes (RTCs) (machine-learning schemes). The first category's contribution is deriving the image's atmospheric effects and removing them from the top-of-atmosphere signal. For instance, to remove atmospheric effects from MSI images, a toolbox including a Sen2Cor processor can be applied to generate MSI land products (Level 2A). Further, this toolbox uses a semi-empirical algorithm that integrates image-based retrievals with Look-Up tables from the LibRadtran model. In the second category, RTCs calculate the scattering and absorption of light via the atmosphere to delete them from the signal estimated by satellite sensors.

Pahlevan et al. (2021) summarized the optical water type specific relative performance of AC processors, using performance matrices guiding the satellite end users. They highlighted the following suggestions to deal with AC methods' performance limitations.

1. The need for better aerosols indicator, absorbing ones in particular.
2. Advancements in corrections for the sky- (or sun-) glint.
3. Adjacency effects.

Our review demonstrates that most of these RS-based cyanoHABs services use Level 1 top-of-atmosphere or simple Rayleigh-corrected quantities. It is because that large uncertainties in Level 2 satellite products affected by insufficient AC performance across eutrophic waters (Binding et al., 2021; Matthews and Bernard, 2013; Schaeffer et al., 2018; Pahlevan et al., 2021). However, the discussion on the AC application for reliable monitoring of inland and coastal waters in different cases (local and global models) follows this later.

4.7.3. Instrument and sensor types for smaller water bodies

The detection of cyanoHABs in inland and coastal waters is challenged by the complexity of the relationship between *in-situ* Chla concentration and Chla indices estimated from satellite measurements (Khan et al., 2021; Coffer et al., 2021). The use of RS algorithms to quantify Chla in optically complex waters dates back to the 1990s (Bukata, 1995; Gitelson, 1999), while it was only towards the end of the MERIS mission lifetime (Moses et al., 2012) that these algorithms became publicly available (Palmer et al., 2015). The advent of high-resolution sensors, such as MSI (10 m) with a similar design and requirements of MSI to the Operational Land Imager on-board Landsat-8, and OLCI (300 m-as a replacement for MERIS), has significantly improved cyanoHABs monitoring (Drusch et al., 2012; Pahlevan et al., 2017; Segl et al., 2015) (Table 1). In particular, OLCI is the only sensor with a spectral band at 620 nm wavelength, which is crucial for PC detection (Schalles and Yacobi, 2000). However, the application of these satellites in smaller water bodies remains challenging due to 'adjacency effects' (Bulgarelli et al., 2014), where mixed reflectance from shorelines can impact the water pixels monitored by satellites (Coffer et al., 2021). Thus, OLCI and MSI have the potential to play a crucial role in overcoming these challenges and improving cyanoHABs detection in smaller water bodies (Khan et al., 2021).

Recall that small water bodies have been the focus of recent studies on cyanoHABs services, which have mainly utilized MSI and OLCI (Cao et al., 2019; Pahlevan et al., 2014; Xu et al., 2020). MSI performs effectively in small water bodies, offering a sub-weekly temporal resolution that is particularly useful at higher latitudes (Li et al., 2017). Besides freely available Sentinel missions' data (Zhu et al., 2019), MSI's radiometric quality, including absolute and relative calibration and signal-to-noise ratio, is considered suitable for cyanoHABs detection using RS (Helder et al., 2018; Pahlevan et al., 2019). The NDCI method is one of the various cyanoHABs detection methods that have been performed using MSI data (Ansper and Alikas, 2019). However, existing MSI-based methods exhibit limitations when applied at the extremes of the observed Chla range (Dörnhöfer et al., 2016; Toming et al., 2016). On the other hand, although OLCI's performance for Chla estimation has been evaluated in aquatic studies, it still lacks adequate high spatial resolution (<100m) to effectively sample small water bodies (Ansper and Alikas, 2019; Philipson et al., 2014). Note that while OLCI provides a 300-m spatial resolution and diverse spectral bands that can support Chla retrieval in large lakes (Pahlevan et al., 2020), there have

been few studies on fresh waters with a width or length less than a few km (Philipson et al., 2014). Consequently, future studies and services should enhance the combined application of OLCI and MSI for cyanoHABs monitoring in both inland and fresh water bodies (Pahlevan et al., 2020).

Moving forward, recently launched hyperspectral satellites, including NASA's hyperspectral satellites, the Plankton, Aerosol, Cloud, ocean Ecosystem (PACE; <https://pace.gsfc.nasa.gov>) mission, would substantially open multiple avenues of research for cyanoHABs monitoring, detection, and reveal ecological and biogeochemical processes in inland waters (Cetin et al., 2018). Although PACE promises to deliver the most spectrally rich global ocean color measurements in NASA's history, its nominal (nadir) resolution (~1.2 km) is the main challenge for small water bodies.

Our results demonstrate that the first step in all operational services is to use L_t at specific wavelengths. Then the effects of the atmosphere are removed, often using atmospheric processors to estimate remote sensing reflectances (R_{rs}). R_{rs} is estimated as the ratio of water-leaving radiance to downwelling irradiance just above the air-water interface. Further, the correction associated with the solar zenith angle and viewing direction can be applied to R_{rs} values to account for the effects of bidirectional reflectance distribution functions (e.g., Morel et al., 1995). Note that, despite water-leaving radiance being attenuated by the atmosphere through its path to top-of-atmosphere, satellite observations still contain information regarding phytoplankton biomass, colored dissolved organic matter, and non-algal particles (Babin et al., 2003).

Next, a wide range of algorithms, such as semi-analytical, empirical, or machine-learning (ML) models, can be utilized to retrieve Chla from reflectance measurements (Carder and Steward, 1985; Morel, 1980; Odermatt et al., 2012). Several models, ranging from semi-analytical and empirical to ML, are available for retrieving Chla in smaller water bodies, specifically from current Sentinel missions (Ansper and Alikas, 2019; Cao et al., 2020; Pahlevan et al., 2020; Smith et al., 2021). Studies suggest that applying the red-NIR spectral regions in freshwater with severe blooms, where Chla absorption and fluorescence peaks are at ~670 nm and 683 nm, respectively. In such cases, colored dissolved organic matter and non-algal particle absorption and its backscattering impacts on the accuracy of algorithms might be insignificant or spectrally invariant (Gitelson, 1999; Gitelson et al., 2007). Our review reveals the application of such models (e.g., NDCI) in most services. However, models that are built upon red or NIR bands often have less sensitivity to uncertainties in AC (Moses et al., 2009). Further, these models' performance relies on the range of Chla variability, the influences of other constituents such as non-algal particle backscattering, and the band configuration of sensors.

To elaborate further, Chla retrieval models are divided into regional, which are fine-tuned for specific water bodies using machine learning for higher precision in cyanoHABs detection (Lehmann et al., 2023; Chegoonian, 2022), and global models, which utilize wide-ranging datasets for broader assessments but may miss local details (Pahlevan et al., 2020; Doeffler and Schille, 2010). The selection depends on the application scope and environmental conditions (Cao et al., 2020; Xue et al., 2019).

5. Socio-economic benefits of cyanoHABs services

Several studies reported that satellite-based cyanoHABs services contributed to informing management decisions (Valipour et al., 2020; Binding et al., 2021; Stroming et al., 2020). The following indicate critical exposure routes of socioeconomic impacts of cyanoHABs services.

5.1. cyanoHABs impact human health through contaminated drinking water

Public Water systems can prevent intact cyanobacterial cells from entering drinking water or reduce the toxins they release. However, during severe bloom events, the increased concentration of cyanobacterial cells or toxins around water intake areas (Falconer et al., 2005; Hoeger et al., 2005; Kouzminov et al., 2007; Qin et al., 2010) can pose difficulties for water system managers to ensure safe and high-quality drinking water to the public (USEPA, 2019).

One reported example is associated with two recent events in Ohio that affected the risk of cyanotoxins contaminating drinking water. In 2013, the Ohio Environmental Protection Agency (Ohio EPA), revealed significant levels of toxins in the local drinking water facility of Carrol Township containing 2000 residents and issued a "Do Not Drink" advisory (Jochem, 2017). In Toledo, significant microcystin levels in the water supply in 2014 caused city officials to issue a drinking water advisory for the entire city, which consists of 500,000 residents, to use bottled water for three days (Fitzsimmons, 2014). Despite that, the Centers for Disease Control and Prevention (CDC) recorded 110 cases of illness related to cyanotoxins from the Toledo event, in which acute gastrointestinal illness was reported as the most common symptom (Benedict et al., 2017).

Wu et al. (2021), assessed if cyanobacterial blooms were related to more emergency room visits for gastrointestinal (GI), respiratory, and dermal illnesses. The study area contained the city of Boston and other cities and towns in the Boston Metropolitan Area that receive municipal drinking water from the Massachusetts Water Resources Authority (MWRA) sourced from the Wachusett Reservoir. They selected twenty two towns located within 20–35 miles (32–56 km) of the reservoir intake, to have the same water residence times of approximately two days in the drinking water distribution system. They evaluated images of MERIS aboard the ESA's Envisat satellite-derived cyanobacteria cell concentrations, employing a retrieval algorithm similar to the one used by the CyAN service in the source of drinking water from 2008 to 2011. Daily counts of hospital emergency room visits for GI, respiratory, and dermal illnesses among drinking water recipients collected from an administrative record database were used for health data. The highest cyanobacteria concentration (above the 75th percentile) was linked to an increase of 4.3 additional cases of respiratory illness (95% confidence interval: 0.7, 8.0, $p = 0.02$, $n = 268$) compared with cyanobacteria concentrations below the 50th percentile in a two-day lag. This indicates a correlation between elevated cyanobacteria levels and respiratory health impacts. The results showed no significant connections between satellite-derived cyanobacterial concentrations and data on GI or dermal illnesses.

5.2. Health risk through food consumption

Toxins may cause a health risk through food consumption by bioaccumulating in seafood from marine and freshwater environments (Ibelings and Chorus, 2007; Poste et al., 2011; Schmidt et al., 2013). Some studies demonstrate that crops irrigated with water affected by CyanoHABs can absorb cyanotoxins. In comparison, there is limited research on associated health risks (Corbel et al., 2014; Lee et al., 2017). Many cyanoHABs-related illnesses have considerable diagnostic ambiguity and a substantial degree of underreporting (Fleming et al., 2011; Grattan et al., 2016; Knaack et al., 2016; Sobel and Painter, 2005). Management and supportive care are the only treatments available for cyanoHABs-related toxin exposures if someone has been diagnosed because of the absence of an antidote. Therefore, illness prevention in these cases is of the highest priority in managing cyanoHABs-related human health risks.

New studies provide targeted suggestions for the early detection and prevention of cyanoHABs-related illnesses based on the associated major toxins for each syndrome. Among them are coastal water monitoring, seafood, and/or shellfish, harvesting beach closures, and rapid illness reporting. However, water and coastal monitoring are reported as the common suggestion for all cyanoHABs-related illnesses.

5.3. Recreation

Toxic cyanobacterial blooms may lead to human health risks from recreation in CyanoHABs-affected water. Despite regularly reported, unscientific evidence related to dermal cyanobacteria in recreational waters (Stewart, 2004; WHO, 2003), more scientific research is needed. A notable exception is the work by Storming et al. (2020), which includes a quantitative assessment of the socioeconomic benefits of EO-based cyanoHABs monitoring for environmental managers and end-users, termed an 'impact assessment' framework. They used this framework to estimate the socioeconomic benefits of applied satellite-based data to manage a 2017 CyanoHABs event in Utah Lake. They reported that the application of satellite data enhanced socioeconomic benefits by improving human health yields valued at approximately \$370,000. Yet a sensitivity analysis elaborates that this central estimate can change significantly (\$55,000–\$1,057,000 in benefits) due to different assumptions associated with the following factors time delay in delivering a recreational advisory.

- The number of people affected by the CyanoHABs,
- The number of people who experience gastrointestinal symptoms, and
- The cost per case of illness.

5.4. Hypoxia and ecosystem health

Even nontoxic blooms negatively influence socioeconomic status through hypoxia and increasing water turbidity, degrading ecosystem services. Chronic hypoxia and water turbidity may adversely affect recreational fishing industries and reduce waterfront property values (Wolf et al., 2017; Wolf and Klaiber, 2017; Zhang and Sohngen, 2018; Stroming et al., 2020). The negative socioeconomic public impact associated with high turbidity and total organic carbon in water can manifest itself through an increase in the price of potable water and disinfection by-product production and create taste and odor problems for drinking water (Cheung et al., 2013; Stroming et al., 2020).

The utilization of EOLakeWatch products has been instrumental in addressing the challenges of hypoxia and deteriorating ecosystem health highlighted earlier. These products are vital in developing and validating coupled hydrodynamic-ecosystem models. Such models have been crucial for scenario-based modeling, supporting ECCC's Lake of the Woods nutrient target setting (Valipour et al., 2020; Binding et al., 2021), which is directly related to mitigating the negative impacts of hypoxia and turbidity on socioeconomic status. Further, the annually reported model-based and satellite-derived algal bloom indices from EOLakeWatch are vital for understanding the benefits of enhanced nutrient management operations. These efforts align with and support the Government of Canada's water-resource management initiatives (Binding et al., 2021). The role of EOLakeWatch in contributing to key agreements such as the Canada-Ontario Agreement on Great Lakes Quality and Ecosystem Health, GLWQA, and the Canada-Manitoba Memorandum of Understanding Respecting Lake Winnipeg and the Lake Winnipeg Basin (ECCC, 2018) further underscores its significance in the broader context of ecosystem health and management.

5.5. Limitations and benefits

5.5.1. Limitations

Although we have outlined several societal benefits, it is important to acknowledge certain general limitations that are common across all RS-based cyanoHABs monitoring services. These limitations may have an impact on the effectiveness and reliability of the data obtained from these services (Table 1). Some of the key limitations include.

- 1 The missing data in individual scenes due to partial swaths, cloud cover, lake ice, and other data-quality concerns diminish the frequency of available data for any given pixel.
- 2 Satellite-based cyanoHABs detection data only cover the horizontal scale of water bodies providing the cyanoHABs data for the surface of the water column. Therefore, there needs to be more information on the vertical distribution of cyanoHABs in the water column (Coffer et al., 2020).

- 3 The lack of consistent and continuous time series of observations. Although the suitable and robust ecological indicator contains a consistent and continuous time series of observations, there is a data gap over the years 2012–15 between the MERIS and OLCI missions. Similarly, algal bloom indices calculated from current instruments have neither the exact spatial resolution nor the same spectral band properties. They need significant validation efforts to establish continuity in bloom reporting.
4. Despite the high spatial resolution of new satellite products, the reduced image frequency can affect the classification of bloom severity.
5. There is no fixed standard or guideline, like Chl_a value, for detecting cyanoHABs, and the definition of a bloom can vary depending on the circumstances.
6. The challenge of minimizing cloud-related artifacts (e.g., cloud edges and cloud shadows).
- 7 One of the significant sources of ambiguity in the detection of cyanoHABs is the intricate relationship between the *in-situ* Chl_a and Chl_a indices derived or estimated from satellite measurements. It is impacted by the variability of the dissolved and particulate matter concentrations affecting the remote sensing reflectance signal. It is vital to advance the development of Chl_a retrieval algorithms for satellite-based cyanoHABs detection operational systems (Cole and Cloern, 1987; Gitelson et al., 2007; Pahlevan et al., 2022).
8. Accurate atmospheric and glint correction prevents a more reliable use of remote sensing reflectance as input to Chl_a or PC retrieval algorithms. The adjacency effect over smaller lakes also introduces errors by influencing reflectance near lake edges, affecting algorithm accuracy.

5.5.2. Specific limitations

CYABI relies on historical satellite-derived data, which limits its use in regions without long-term datasets, including the FCA index. CyanoTRACKER suffers from unreliable Twitter data representation, missing downwelling irradiance sensors, and poor data transfer due to weak cell networks.

EOLakeWatch's specific limitations are data gaps, cloud cover-induced variability, inconsistent bloom detection, and underestimation of Chl_a at high concentrations.

GEE-based Services: Computational constraints hinder efficient long-time-series analyses over large water bodies.

5.5.3. Benefits

Despite the general limitations faced by all services, the specific benefits of each service are distinct and warrant detailed discussion. These benefits highlight the unique contributions and advancements each service brings to the field of cyanoHABs monitoring. Detailed below are the specific benefits offered by each service.

5.5.3.1. Cyabi.

- Offers adaptable monitoring through various data sources, which saves on needing multiple tools.

5.5.3.2. CyAN.

- Simplifies satellite data use for water quality management, reducing training costs.
- Provides cost-effective CyanoHABs data management for multiple water bodies.
- Allows setting of cyanobacteria alerts, leading to cost-effective early detection.
- Accelerates health advisories with timely cyanoHABs warnings, reducing health and cleanup costs.
- Delivers data in user-friendly formats, lowering the need for specialized training.

5.5.3.3. EOLakeWatch.

- Encourages community involvement in satellite data monitoring, cutting down on professional monitoring costs.
- Combines multiple indices for accurate toxicity assessments, potentially decreasing sampling costs.
- Integral in model validation for nutrient management, aiding in cost-saving environmental policy-making.
- Indices from EOLakeWatch inform nutrient management effectiveness, supporting cost-effective watershed management.

5.5.3.4. CyanoTRACKER.

- Enables local monitoring of cyanoHABs, involving community groups for cost-saving measures.

5.5.3.5. *AlgaeMAP*.

- Provides high-resolution monitoring within the GEE platform, which saves on computational resources and the need for advanced skills.

5.5.3.6. *CyanoKhoj*.

- Utilizes the GEE platform for detailed, accessible monitoring, saving computational costs and simplifying data analysis.

Each tool's design emphasizes cost reduction through efficiency, accessibility, and community engagement in environmental monitoring efforts. We note that Google Earth Engine (GEE), used by three of the six monitoring systems, is free for non-commercial use ([Google Earth Engine, n.d.](#)).

6. Research directions

6.1. Algorithmic approach and accuracy

The accuracy of cyanoHABs detection approaches depends on multiple factors, i.e., data collection methodology, satellite imagery, pre-processing, and the number of samples performed for calibration and validation ([Neil et al., 2019](#)). Therefore, a direct performance comparison among cyanoHABs estimation methods is almost impossible. The existing literature must show consistent results when comparing analytical and empirical methods for studying water-light interaction. Some studies report that semi-analytical methods are more apt ([Ali et al., 2014](#); [Sarangi, 2012](#)), while others suggest that empirical methods are superior ([Sagan et al., 2020a](#)), and there are also studies indicating that both methods yield similar results ([Allan et al., 2015](#)). This makes it difficult to draw definitive comparisons between the two methodological categories. However, many studies have shown unparalleled advantages of machine learning approaches for water quality mapping, including cyanoHABs detection ([Peterson et al., 2020](#); [Sagan et al., 2020a](#)). An upward accuracy trend has been observed utilizing machine learning methods compared to conventional models ([Kim et al., 2019](#); [Sagan et al., 2020a](#)). To diminish the challenge of optical complexity, we suggest prioritizing the employment of emerging technology and machine learning in case of available reference routinely monitored data. For example, the machine-learning model, the Mixture Density Network (MDN) advocated by [Pahlevan et al. \(2020\)](#), has been shown to be robust across a wide range of trophic states.

6.2. Universal threshold of bloom formation

Defining a universal threshold of increased algal biomass to form a bloom is challenging. The Lake Dianchi study, utilizing a 34-year remote sensing dataset from Landsat and MODIS imagery with the Floating Algae Index (FAI), reveals that bloom formation thresholds vary according to environmental conditions like season, wind speed, and air temperature, with peak bloom occurrences in the rainy season and higher frequencies in northern regions ([Ma et al., 2022](#)). This highlights the complexity of defining a universal bloom formation threshold. Thresholds for bloom detection are further complicated by the intended use of the water body (e.g., drinking, recreation), which affects acceptable biomass levels and can change over time. However, when assessing the situation, note that the threshold value should be selected based on the most recent WHO guidelines ([World Health Organization, 2021](#)). Nevertheless, this threshold to identify the bloom on a pixel-by-pixel basis for cyanoHABs-related studies is highly variable and impactful on derived bloom statistics.

6.3. Emerging technologies and democratization of data and information as a way forward

The variance of documented bloom indices extracted from daily imagery depends mainly on the availability of reliable data. The variety is caused by cloud-induced data gaps together with the natural dynamic nature of blooms. Therefore, recently, the need for frequent cyanoHABs observations and reliable documents on seasonal and long-term trends has received further attention in a substantial body of cyanoHABs management strategies and research ([Dierssen et al., 2020](#)). Detail-oriented presentation of validation data based on a standard protocol of the parameters of interest, generally including the source of data sampling, period, number of stations and samples, laboratory analysis, applied in situ reflectance instrument, and a split ratio of data for calibration and validation. However, we encourage unified effort by empiricists, theoreticians, and cyanoHABs detection scientists to share the data, knowledge, and information, including compiled water quality reference data from government agencies ([Shen et al., 2010](#)), field campaigns ([Moses et al., 2012](#)), or existing databases through an ad-hoc, community data sharing activity ([Sayers et al., 2019](#); [Lehmann et al., 2023](#)). We propose the creation of an open-source dashboard as a scientific communication tool to facilitate the global sharing, access, and discussion of cyanoHABs events.

6.4. Satellite technique trade-offs in cyanoHABs analysis

Selecting a technique or satellite product requires careful consideration of various trade-offs associated with the spatial, temporal, and spectral resolution of satellite products and their recorded period. The consequence of these choices for cyanoHABs analysis is an emerging field demanding further investigation. However, it is expected that OLCI and MSI open opportunities for the science community to invent enhanced methods for retrievals of Chla and other water constituents (Ansper and Aliakas, 2019; Cazzaniga et al., 2019; Gernez et al., 2017; Toming et al., 2016). The users must be cautious in interpreting satellite-based time series observations such as Landsat and Sentinel-2 MSI with noticeably reduced revisit times of 16 and 10 days, respectively (Ho et al., 2019; Feng et al., 2020). Despite offering significant benefits of higher spatial resolution, reduced image frequency raises red flags in misclassifying bloom severity compared with near-daily observations provided by OLCI. Further, the spectral capabilities of each sensor type influence CyanoHABs detection accuracy; for example, sensors designed for ocean color can better detect specific Chla concentrations but may lack the versatility needed across diverse aquatic environments. PACE, already in orbit, provides daily global hyperspectral data for large-scale trends, while upcoming missions—Geostationary Littoral Imaging Radiometer (GLIMR) for frequent coastal monitoring and Surface Biology and Geology (SBG) for high-detail inland analysis—complement PACE's capabilities (Dierssen et al., 2023). Together, they balance trade-offs, enhancing CyanoHABs monitoring across different aquatic environments.

6.5. Global applicability among reviewed services

Among the reviewed services, the CyAN system is currently the only widely used and validated satellite-derived application implemented across many freshwater ecosystems (approximately 2000) within the Continental United States. Applying such a system globally requires extensive validation efforts, noting that different countries have their own technical/cultural approach to monitoring HABs.

7. Conclusion on the Perceived impact of the proposed cyanoHABs monitoring operational Service

In conclusion, the significance of satellite-based cyanoHABs monitoring services such as CyAN, CyanoTRACKER, EOLakeWatch, and CyanoKhoj in addressing the challenges posed by cyanoHABs cannot be overstated. These services have transformed how cyanoHABs are detected, monitored, and managed, leveraging the latest advancements in satellite imagery and data analysis to provide comprehensive, accurate, and timely insights into cyanobacterial bloom dynamics across diverse water bodies.

CyAN has been instrumental in enhancing water quality management through its sophisticated use of satellite data, which reduces training costs and provides a cost-effective approach to CyanoHABs data management. Its alert system for cyanobacteria presence facilitates early detection and rapid response, accelerating health advisories and minimizing health and cleanup costs.

CyanoTRACKER has successfully harnessed community involvement in cyanoHABs monitoring, leveraging localized data collection and analysis to engage community groups in cost-saving measures. This participatory approach has significantly enhanced the effectiveness and responsiveness of cyanoHABs management strategies.

EOLakeWatch has further underscored the importance of community engagement by promoting satellite data monitoring at a community level, thereby reducing professional monitoring costs. It has made significant strides in combining multiple indices for accurate toxicity assessments, contributing to cost-saving environmental policy-making and effective watershed management.

CyanoKhoj stands out for its innovative use of the GEE platform to provide detailed and accessible monitoring capabilities. By facilitating high-resolution monitoring and simplifying data analysis, CyanoKhoj plays a crucial role in advancing the field of cyanoHABs detection. Its ability to harness the computational power of GEE for analyzing extensive datasets makes it a valuable tool in the ongoing efforts to develop more efficient and effective cyanoHABs monitoring applications.

Although Cyabi has demonstrated potential, especially in areas such as the Gulf of Finland, by incorporating satellite-derived data into a comprehensive index for evaluating ecological status, its wider application and improvement could greatly benefit from the methods and achievements of CyAN, CyanoTRACKER, EOLakeWatch, and CyanoKhoj.

The ongoing development and integration of these satellite-based monitoring services are set to enhance our capability to identify, manage, and mitigate the effects of cyanoHABs. Using the strengths and innovative methods of services like CyAN, CyanoTRACKER, EOLakeWatch, and CyanoKhoj, the field is well-positioned to make significant progress in protecting water quality and ecosystem health worldwide.

Nevertheless, besides traditional field sampling and laboratory analysis limitations, they are indispensable for detecting toxic species that trigger cyanoHABs alert thresholds and for species-specific toxin confirmation tasks that remote sensing alone cannot achieve. We highlight the complementary nature of remote sensing in expanding the spatial and temporal coverage of monitoring efforts, particularly in areas where field sampling is limited due to logistical or resource constraints.

CRedit authorship contribution statement

Nasim Janatian: Writing – review & editing, Writing – original draft, Visualization, Methodology, Formal analysis, Conceptualization. **Urmaz Raudsepp:** Writing – review & editing, Supervision, Conceptualization. **Parya Broomandi:** Writing – review & editing, Writing – original draft, Formal analysis. **Kate Fickas:** Writing – review & editing. **Kalle Olli:** Writing – review & editing. **Timo Heimovaara:** Writing – review & editing. **Aarne Mannik:** Writing – review & editing. **Rivo Uiboupin:** Writing – review & editing. **Nima Pahlevan:** Writing – review & editing, Supervision, Methodology, Conceptualization.

Consent to participate

Not applicable.

Ethical Approval

Not applicable.

Consent for publication

Not applicable.

Ethical Statement

This statement accompanies the article “**A review on remote-sensing-based harmful algal bloom monitoring services**” authored by Nasim Janatian and Nima Pahlevan and co-authored by Urmas Raudsepp, Parya Broomandi, Kate Fickas, Kalle Olli, Timo heimovaara, Aarne Mannik, Rivo Uiboupin, submitted to *Remote Sensing Applications: Society and Environment* as an Article Type.

Hereby, we consciously assure that for the manuscript “**A review on remote-sensing-based harmful algal bloom monitoring services**” the following is fulfilled.

- 1) This material is the authors’ own original work, which has not been previously published elsewhere.
- 2) The paper is not currently being considered for publication elsewhere.
- 3) The paper reflects the authors’ own research and analysis in a truthful and complete manner.
- 4) The paper properly credits the meaningful contributions of co-authors and co-researchers.
- 5) The results are appropriately placed in the context of prior and existing research.
- 6) All sources used are properly disclosed (correct citation). Literally copying of text must be indicated as such by using quotation marks and giving proper reference.
- 7) All authors have been personally and actively involved in substantial work leading to the paper, and will take public responsibility for its content.

We agree with the above statements and declare that this submission follows the policies of as outlined in the Guide for Authors and in the Ethical Statement. We affirm that the research has been conducted with the utmost respect for ethical standards, and we are committed to the responsible dissemination and application of our findings for the benefit of society and the environment.

Declaration of competing interest

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

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Appendix B. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.rsase.2025.101488>.

Appendix A**Table A1**

Sensor characteristics.

	Nominal spatial resolution (m)	Swath width (km)	Useable Spectral bands for Chla (nm)
<i>MultiSpectral Instrument (MSI)</i>	10, 20, 60	290	443, 492, 560, 665, 705, 740, 783)

(continued on next page)

Table A1 (continued)

	Nominal spatial resolution (m)	Swath width (km)	Useable Spectral bands for Chla (nm)
<i>Ocean Colour Land Instrument (OLCI)</i>	300	1270	410, 443, 490, 510, 560, 620, 665, 673, 681, 708, 753, 778
<i>Medium Resolution Imaging Spectrometer (MERIS)</i> <i>(Moderate Resolution Imaging Spectroradiometer (MODIS))</i>	300 500, 1000	1150 2330	412, 442, 490, 510, 560, 620, 665, 681, 709, and 754 469, 488, 531, 547, 555, 645, 667, 678, and 748

CyanoTRACKER

Note that the absorption feature near 620 nm has been mainly used to detect CyanoHABs and determine PC concentration (Simis et al., 2005; Mishra et al., 2009; Ogashawara et al., 2013; Page et al., 2018). Further, the detailed methodology for this service includes the following:

CyanoSense has the STS-VIS hyperspectral spectroradiometer (OceanOptics, Largo, FL), which can detect the presence of Chla and PC at their characteristic absorption wavelengths (665 nm and 620 nm, respectively). First, CyanoSense data are filtered for noise like saturation or spikes by comparing the light intensity spectrum between 450 and 700 nm.

2. To establish an empirical relationship between band-specific reflectance and PC, and Chl-a remote sensing reflectance (R_{rs}), data are used by CyanoSense. R_{rs} is estimated using radiometric quantities (L_{sky} , L_w , and L_c) following the cross-calibration as below:

$$R_{rs} = L_w - \frac{(0.02 \times L_{sky})}{(1.01 \times \pi \times L_c)} \quad (A1)$$

3. Once R_{rs} is derived, PC (Mishra and Mishra, 2014; Chla Mishra and Mishra, 2012) are estimated

$$PC(\mu g / L) = 476.33 \times PC_3 + 96.16 \quad (A2)$$

where

$$PC_3 = \left[\frac{1}{R_{rs}(629)} - \frac{1}{R_{rs}(659)} \right] \times R_{rs}(724), \quad (A3)$$

$$Chla(\mu g / L) = 194.325 \times [NDCI]^2 + 86.115 \times NDCI + 14.039 \quad (A4)$$

where

$$NDCI = \frac{R_{rs}(708) - R_{rs}(665)}{R_{rs}(708) + R_{rs}(665)}. \quad (A5)$$

EOLakeWatch

The MCI captures the red-edge reflectance feature associated with dense surface algal blooms. *Chla*, *MCI*, and *MCI_Slope* were calculated as below:

$$MCI = L_{t(\lambda_2)} - L_{t(\lambda_1)} - \frac{\lambda_2 - \lambda_1}{\lambda_3 - \lambda_1} \times [L_{t(\lambda_3)} - L_{t(\lambda_1)}] \quad (A6)$$

$$MCI_Slope = \frac{L_{t(\lambda_3)} - L_{t(\lambda_1)}}{\lambda_3 - \lambda_1} \quad (A7)$$

$$Chla = 6.166 \times MCI + 6.347 \quad (A8)$$

where for both MERIS and OLCI, λ_1 , λ_2 , and λ_3 were centered at 681, 708, and 753 nm, respectively.

AlgaeMAP (Algae Bloom Monitoring Application)

To mask out the pixels with clouds and water, the Cloud Probability product and the Joint Research Centre (JRC) Water Mask product available on GEE were used (33). After completing pre-processing steps, the NDCI was calculated as below (Mishra and Mishra, 2012; Lobo et al., 2021):

$$NDCI_{sat} = \frac{(R_{rs(705)} - R_{rs(665)})}{(R_{rs(705)} + R_{rs(665)})} \quad (A9)$$

For Sentinel-2, the $R_{rs(705)}$ and $R_{rs(665)}$ are the central wavelengths for Surface Reflectance at 705 nm and 665 nm, corresponding to Band 5 (red edge) and Band 4 (red), respectively.

To derive the Chla algorithm, once $NDCI_{sat}$ and in situ Chla data ($N = 136$, for a two-days time window) were matched up, the Monte Carlo model was applied. Therefore, the validated power-law fitting curve ($N = 30\%$) predicts Chla concentrations ($\mu\text{g/L}$) as below:

$$Chla = 23.44 \times (NDCI_{sat} + 1)^{7.95} \quad (\text{A10})$$

The final predictive model presented a $R^2 = 0.86$ and MAPE close to 90%. The low indicated accuracy by MAPE could be due to associated uncertainties with the proposed algorithm in Chla values below 5 $\mu\text{g/L}$ and above 70 $\mu\text{g/L}$. The algorithm can accurately estimate medium to high Chla concentrations between 10 and 70 $\mu\text{g/L}$ (Lobo et al., 2021).

According to Chla concentration, the Trophic State Index (TSI) can be classified into six classes, ranging from Ultra-oligotrophic to Hyper-eutrophic. The $NDCI_{sat}$ distributions were statistically different between all classes, except for Ultra-oligotrophic, reclassified into Oligotrophic. $NDCI_{sat}$ threshold, which classifies into five TSI levels, was determined using a decision tree based on the Monte Carlo technique. To detect the presence of algae bloom (AB), both Hyper-eutrophic levels were considered as algae bloom conditions (i. e., $Chla > 30.55 \mu\text{g/L}$) (Lobo et al., 2021). In contrast, non-bloom conditions were considered Oligo, Meso and Eutrophic levels. According to the results, $NDCI_{sat}$ thresholds (nodes) were: <Oligo (-0.131), <Meso (-0.093), < Eutrophic (0.025), and <Hyper (0.127). The Gini index indicates high purity for the Hypereutrophic class ($n = 23$) (Lobo et al., 2021). Generally, results showed a satisfactory performance which lets the end-user detect increasing levels of eutrophication (Lobo et al., 2021).

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$$NDCI = \frac{\rho_{rc}(709) - \rho_{rc}(665)}{\rho_{rc}(709) + \rho_{rc}(665)} \quad (\text{A11})$$

$$Chla (\mu\text{g} / \text{L}) = 194.325 \times NDCI^2 + 86.115 \times NDCI + 14.039 \quad (\text{A12})$$

$$SS(681) = \rho_{rc}(681) - \rho_{rc}(665) - [\rho_{rc}(709) - \rho_{rc}(665)] \times 0.3636 \quad (\text{A13})$$

$$CI = -1 \times SS(681) \quad (\text{A14})$$

$$SS(665) = \rho_{rc}(665) - \rho_{rc}(620) - [\rho_{rc}(681) - \rho_{rc}(620)] \times 0.7377 \quad (\text{A15})$$

$$\text{If } SS(665) > 0 \text{ then } CI = CI_{cyano} \quad (\text{A16})$$

$$CCD (\text{cells} / \text{mL}) = CI_{cyano} \times 10^8 \quad (\text{A17})$$

Where:

$NDCI$ is normalized difference chlorophyll index; Chla is Chlorophyll-a; $SS(681)$ is Spectral Shape at 681 nm; $SS(665)$ is Spectral Shape at 665 nm; CI is Cyanobacteria Index; CI_{cyano} is Cyanobacteria Index specific to cyanobacteria only; CCD is cyanobacteria cell density or cyanoHAB abundance.

ρ_{rc} Rayleigh corrected reflectance

ρ_T TOA reflectance

Data availability

No data was used for the research described in the article.

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