1. **Monitoring Harmful Algal Blooms in Singapore: Developing a HABs Observing System**

Abstract

There is enhanced interest in monitoring and detecting of HABs. An attack leads to massive fish kills and great economic losses. Interdisciplinary approach involving:

* Robotic network adaptation,
* Multi-scale-sensing using autonomous vehicles
* in-situ and
* Real time multidisciplinary data acquisition using unmanned and wireless network

Can be utilized to study and monitor HABs in waters. The study managed to collect high spatial resolution data using.

*Low salinity* was observed near the mouth of the reservoir, and the salinity increased with increasing distance from the reservoir mouth. In contrast, *high phytoplankton biomass* was observed near the reservoir mouth, while lower concentration was found further away from the mouth. This information could assist in *defining bloom parameters* and enhance our ability in determining and detecting pre-bloom condition. In addition, the ASV platform used in this study could assist in collecting high spatial resolution data set, which was not possible with point sampling. The information provided by the present study can assist in refining of bio-optical models for detecting and monitoring of HABs.

Introduction

The magnitude and the duration of a bloom may also determine the degree of impact on an ecosystem. Detecting and monitoring of algal blooms in selected waters are essential to describe the trends of blooms, and thus providing a means for protecting the aquatic ecosystem and public health. The specific causes of HABs are complex, and they vary between species and locations, and are not all well understood.

The detection and monitoring of HABs in a given ecosystem might be challenging due to *regular eutrophication events and high levels of sediments in the water column*. These characteristics make traditional optical and satellite detection methods somewhat unreliable.

Multidisciplinary data and high spatial resolution data sets are essential to observe the oceanographic processes and dynamics of algal blooms in this area. The focus of the present study was to develop mobile sensor networks for monitoring HAB events, formation and the biology of bloom-forming species in Singapore waters.

II. Materials & Methods

Interdisciplinary Approach

The study used a tiered adaptive network for multi-scale sensing, which involved a robotic network adaptation, multi-scale-sensing using autonomous vehicles and in-situ and real time multidisciplinary data acquisition using unmanned and wireless network.

The network consists of ships, fixed instruments, and autonomous vehicles (unmanned aerial vehicle (UAV), autonomous surface vehicle (ASV), autonomous underwater vehicle (AUV).]

Conditions include areas with:

* Possible nutrient input from terrestrial sources,
* Freshwater input and
* Areas with minimum water movement.

III Data Collection and Measurements

*Tiered adaptive network for multi-scale sensing* was used to measure environmental parameters. Areas around a targeted station or area was monitored using UAV. Then the ASVs and AUVs mounted with multiples sensors were deployed accordingly for data collections. Experimental trials were conducted every six months from Dec 2010 to Jan 2012.

The following parameters;

* Temperature,
* Salinity,
* Chlorophyll (chl)-a and
* Dissolved oxygen was measured.

Time series measurements were conducted from Sept 2010 to Jan 2012 at stations. Physical parameters were measure at site.

Sea water samples for:

* Nutrients,
* pigments (chl-a) and
* colored dissolved organic matter (CDOM), were collected from the surface water a clean bucket.

IV. Data Preparation and Analysis

Contour maps are created using ocean data view. *The salinity was lower at the outlet of the Reservoir as compared to salinity measured further away from the reservoir outlet*. (Show maps) On the contrary, *biomass as indicated by chl-a concentration showed a decreased in concentration with increasing distance from the reservoir’s outlet* (Show maps) A significant relationship between salinity and chl-a was found. Similar trend between *salinity and chl-a* was also observed from phytoplankton assemblage from other study areas. This observation suggests that salinity might be an important factor regulating the phytoplankton biomass. *The salinity level might also affect the phytoplankton communities, and thus, it should be considered when monitoring and detecting HABs.*

Data measurements were also conducted at different tide i.e., *ebb tide vs. flood tide.* During ebb tide, narrower range of variability in both environmental parameters and biological measurement were observed (Map). On the other hand, during flood tide, larger range of fluctuation in parameters was observed*. For example, the chl-a concentration was found to differ around two times between ebb and flood tide*.

*As for the time series experiments*, during the sampling period, it was noted that the concentration of colored dissolved organic matter (CDOM) was very high in the East as shown by *the indicative index CDOM (250)*. *CDOM is known as the main absorber of sunlight and a major factor determining the optical properties of coastal waters.* CDOM can also serve as a source of nitrogen in marine waters. There as well exist significant *relationships of between CDOM and chl-a and salinity*.

It has been consistently observed that the quantity of CDOM shows a negative relationship with salinity (i.e., high concentrations were observed at low salinity). This is because high CDOM is usually associated with low salinity and CDOM is normally originated from freshwater sources.

Low salinity and high CDOM might be some of the conditions necessary for high phytoplankton biomass development as pre-conditions of algal bloom especially toxic HAB.

V. CONCLUSION

Circulation patterns driven by tides play an important role in determining the distribution of phytoplankton biomass and other environmental parameters.

Variability in the biomass could be determined by environmental parameters such as salinity and CDOM. The observed variability of environmental parameters in the present study suggested that the condition of this coastal system is subjected to multiple influences such as the input of terrestrial sources, atmospheric conditions, and tidal currents. Characterization of these parameters could assist in the identification of trends, and the estimation of short and long-term implications of such changes for the environment and society. Moreover, such information could assist in detecting and mitigating HABs. *With more data, algorithm could be fine-tuned to provide a means to interpret field populations and enhance the capability for detecting harmful species*.

1. **The Monitoring of Harmful Algal Blooms through Ocean Observing: The Development of the California Harmful Algal Bloom Monitoring and Alert Program**
2. **A Comprehensive Review on Water Quality Parameters Estimation Using Remote Sensing Techniques \_ Enhanced Reader**
3. **Harmful Algal Blooms Threaten the Health of Communities A Case Study in Kisumu Bay, Lake Victoria, Kenya**
4. **EO Lake Watch; delivering a comprehensive suite of remote sensing algal bloom indices for enhanced monitoring of Canadian eutrophic lakes. –** *Elsevier, Accepted 21 September 2020*

The data and imagery used in this manuscript are available on the EOLakeWatch portal at https://www.canada.ca/en/environmentclimate-change/services/water-overview/satellite-earth-observationslake-monitoring.html and the

Government of Canada open data portal:

https://open.canada.ca/data/en/dataset/4d100a02-1494-452f-9f77- 84258b26e1cd.

Supplementary data to this article can be found online at:

https://doi. org/10.1016/j.ecolind.2020.106999.

Abstract

To address the constantly deteriorating water quality, EOLakeWatch was developed to deliver a suite of useful, easily interpretable, and accessible EO-derived products to support algal bloom monitoring on these three lakes.

Algal bloom indices, *describing bloom spatial extent, intensity, duration, and severity* were derived using the *European Space Agency’s OLCI (Ocean and Land Color Instrument) sensor for observations from 2016 to present and its predecessor MERIS (Medium Resolution Imaging Spectrometer) for 2002 to 2011*

Objectives.

1. To address existing monitoring gaps, by delivering prompt, consistent measures of lake-wide algal bloom conditions required
2. To provide stakeholders with early warning of bloom risks,
3. To identify areas of potential concern,
4. To quantify spatio-temporal trends,
5. To further understand bloom dynamics and drivers.
6. To guide and determine the effectiveness of implemented management actions.
7. Introduction

There is substantial evidence that the frequency and magnitude of harmful algal blooms (HABs) in coastal and inland waters around the world have been increasing, attributed in large part to cultural eutrophication, and climate change (Hallegraef, 1993; Glibert et al., 2005; Paerl and Huisman, 2008; Heisler et al., 2008). Likewise, many freshwater systems in Canada have seen increases in HAB occurrences,

* Posing serious threats to ecosystem integrity
* Significant public health risks (Kling, 1998; Watson et al., 2008; Winter et al., 2011; Stumpf et al., 2012; Pick, 2016).

The proliferation of inland water HABs has a multitude of impacts on ecosystem services;

* From drinking water resources,
* commercial fisheries,
* leisure and recreational activities,
* The generation of hydroelectric power,
* leading to significant socio-economic costs when a waterbody is rendered unsuitable for its wide-ranging uses (Smith et al., 2019).

In most regions of North America, the majority of freshwater planktonic HABs are caused by *cyanobacteria* (Watson et al., 2016; Lopez et al., 2008). Several cyanobacteria taxa have the capacity *to produce potent toxins* that can cause a range of

* hepatic
* neurologic and
* dermatologic effects.

Therefore, raising serious health concerns when they are detected in recreational or drinking water resources*. HABs lower the aesthetic value of waterbodies and by reducing water clarity impact light availability for pelagic and benthic ecosystems*. Upon senescence, blooms contribute to hypolimnetic hypoxia, *causing disruption and mortality to pelagic and benthic biological communities* (Watson et al., 2016).

Lake Winnipeg (LW) is Canada’s sixth largest lake (Fig. 1B); it is a shallow, turbid lake, covering an area of 23,750 km2 with a watershed spanning almost a million square kilometers. LW has experienced accelerated nutrient loading and a dramatic increase in phytoplankton biomass over the last two decades brought about by intensified agricultural practices and livestock production, urban development, and changing hydrology (Kling et al., 2011; Schindler et al., 2012; McCullough et al., 2012; Bunting et al., 2016).

Blooms on LW have been reported to *consist primarily of non-nitrogen-fixing cyanobacteria* (several species of Microcystis and Planktothrix) in the south basin, with the north basin exhibiting reduced taxonomic diversity with a predominance of the nitrogen-fixing cyanobacteria Aphanizomenon flosaquae and Dolichospermum spp. (Kling et al., 2011).

Through the Lake Winnipeg Basin Program (LWBP), ECCC has supported local stewardship action, monitoring, and research activities, to address the impacts of nutrient enrichment and inform watershed-based nutrient-reduction strategies. Targets have been set to reduce phosphorus levels by 50% in an effort to restore lake conditions to a pre-1990 state and reduce the frequency and severity of algal blooms (ECCC, 2013). Lake of the Woods (LoW), is a hydrologically complex lake, consisting of an expansive, shallow and well-mixed bay to the south and a collection of deeper, occasionally stratified interconnected basins. Blooms on Low have typically been dominated by Aphanizomenon except in the deeper northern embayments, where Dolichospermum often predominates (Watson and Kling, 2017).

Despite *reductions in Total Phosphorous loads in the last few decades,* symptoms of eutrophication persist, manifested by ongoing severe cyanobacteria blooms (Anderson et al., 2017) which frequently cover as much as 80% of the lake’s surface (Binding et al., 2011).

*Exacerbating factors* such as

warming temperatures and legacy nutrients stored in sediments are postulated to have, so far, limited a full recovery of the lake (Paterson et al., 2017; Reavie et al., 2017).

*Recently there’s need to create binational phosphorus load reduction t*argets for the lake after the Minnesota portion of LoW was declared impaired for recreational use due to exceedances of eutrophication criteria (Heiskary and Wilson, 2008). Binational efforts in the 1970’s to reduce phosphorous loadings to the lake led to significant declines in phytoplankton biomass but since the early 2000’s, cyanobacteria blooms have once again become a recurring annual event, particularly across the western basin of LE.

Blooms are often reported as heavily dominated by the potentially toxic cyanobacterium Microcystis (Bridgeman et al., 2013; Michalak et al., 2013; Steffen et al., 2014) although others have indicated that the bloom consists of a more diverse community composition (Berry et al., 2016; Davis et al., 2015; Moore et al., 2017; Binding et al., 2019).

The algal bloom of 2014 led to the City of Toledo issuing a drinking water advisory to more than 400,000 residents due to the presence of unsafe levels of the toxin Microcystin (Jetoo et al., 2015). Renewed commitment to remedial action led to binational adoption of targets for a 40% reduction in phosphorus loads compared to a 2008 baseline in order to meet Lake Ecosystem Objectives of levels of algal biomass, species composition and toxin concentrations consistent with a healthy aquatic ecosystem (GLWQA, 2012; Baker et al., 2019).

To varying extents, in situ water quality monitoring is conducted on all three lakes. However, blooms vary from localized to lake-wide events and can be highly dynamic in space and time therefore are difficult to adequately capture with conventional sampling methods collecting discrete water samples (Kutser et al., 2006; Reinart and Kutser, 2006; Kahru et al., 2007).

Even with regular monitoring programs, reliable spatio-temporal analyses are often hampered by fragmented datasets (Dove and Chapra, 2015; Kratzer et al., 2019), while inconsistencies in the timing of surveys make multi-lake or multi-year comparisons a challenge.

This lack of consistent, large-scale, time-series data on the severity of blooms often impedes resolving short- and long-term variance in HAB events and developing robust management strategies for their mitigation.

Earth observation (EO) satellites providing multispectral observations of inland water colour enable *quantitative assessment of algal biomass via estimates of chlorophyll-a concentrations.* Beyond chlorophyll retrievals, EO has been used to deliver quantitative measures *of algal bloom intensity and severity* (Stumpf et al., 2012), *spatial extent* (Urquhart et al., 2017), and *frequency* (Clark et al., 2017).

Satellite observations have increasingly been integrated operationally into inland water algal bloom monitoring, *providing public information and early warning services*, through programs such as the *U.S. National Oceanic and Atmospheric Administration* (NOAA) *HAB Tracker* (Stumpf et al., 2016a), the U.S. Environmental Protection Agency (EPA) CyAN project (Schaeffer et al., 2018), CyanoTRACKER (Mishra et al., 2020) and CyanoLakes (Matthews, 2016).

EO also forms a key component of Baltic Sea *cyanobacterial bloom monitoring, combining estimates* of the areal coverage, duration and bloom severity into the *Cyanobacterial Bloom Index* (CyaBI) as a core eutrophication indicator to evaluate the current bloom status in relation to historical target conditions (Kahru and Elmgren, 2014; Anttila et al., 2018).

In June 2020 ECCC launched EOLakeWatch to deliver a suite of EO-derived algal bloom products of value to water resource stakeholders and the public, and support inland water HAB monitoring and research activities. EOLakeWatch builds on ECCC’s previous work developing and validating algorithms for remote sensing of algal blooms (Binding et al., 2011, 2013, 2018, 2019) to transition to an operational service delivery.

Products are distributed in *near-realtime through a web-based data portal* (EOLakeWatch, 2020).

Image processing workflow

* The suite of indices produced for algal bloom monitoring:
* Documentation of bloom intensity, s
* Spatial extent,
* Duration and
* Severity on each lake since 2002, and (3) an analysis of variability among those indices in capturing bloom conditions on each lake.

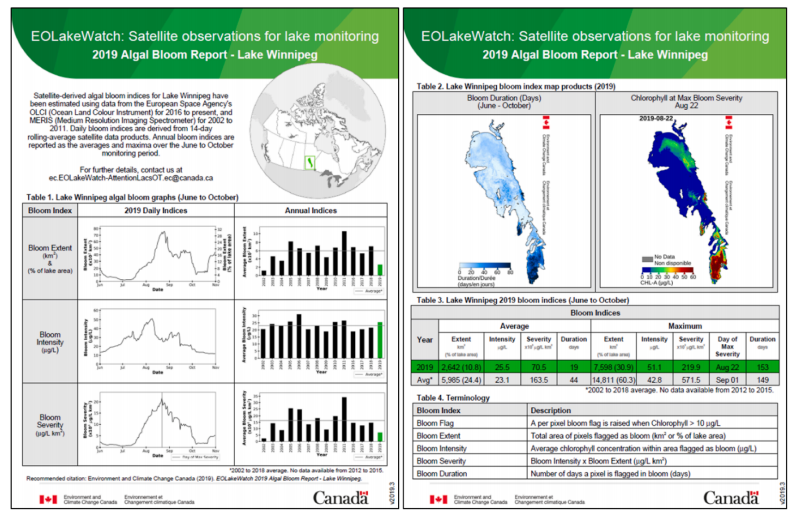
Results

Were discussed in the context of water quality monitoring and management needs and in further understanding environmental drivers of blooms.

**Methods 2.1.**

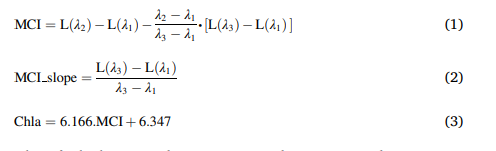
**Image processing workflow**

Algal bloom products were derived using data from the Ocean and Land Color Instrument (OLCI) on the European Space Agency’s (ESA) Sentinel-3A satellite, launched in February 2016, and its predecessor the Medium Resolution Imaging Spectrometer (MERIS) on board ESA’s Envisat, which operated from 2002 to 2011.



**Image Processing Workflow**

* Begins *with the automated download of OLCI Level-1 FR* (full resolution, 300 m spatial resolution at nadir) imagery from the Copernicus Open Access Hub on a daily basis from June 1 to October 31. MERIS Level-1 FR imagery were obtained from ESA’s MERCI online archive (www.merisfrs-merci-ds.eo.esa.int). The *June to October* window captures the majority of the cyanobacteria bloom season on all three lakes, is in line with peak recreational usage and potential socioeconomic impact, and minimizes potential image artifacts brought about by winter lake ice cover.
* *Fully automated image processing* routines were developed, with customized scripts in Python, ESA’s SNAP and QGIS, running on Ubuntu OS.
* True color quick-view images are produced and reviewed for quality assurance.
* Top-of-atmosphere spectral radiance (L(λ)), georeferenced and calibrated to geophysical units (W/m2 /sr/µm), are subset to defined regions of interest for each lake.
* Images are masked according to quality flags (sun glint, duplicate pixels, bright, coastline, or otherwise invalid pixels).
* Chlorophyll retrieval algorithms exploiting the Red-NIR portion of the spectrum perform well in turbid eutrophic waters (Gilerson et al., 2010) and line-height algorithms such as the Maximum Chlorophyll Index (MCI: Gower et al., 2008), are particularly favorable due to their relative insensitivity to uncertainties in atmospheric correction.
* The MCI, quantifies a peak in radiance at 708 nm relative to a baseline interpolated between bands either side, capturing the red-edge reflectance feature associated with dense surface algal blooms. MCI, MCI\_slope and Chlorophyll-a concentrations (Chla) are calculated according to Eqs. (1), (2) and (3) respectively.
* MCI\_slope is used to mask extreme sediment events, which have been shown to lead to *potential false positive bloom detection* in red-NIR *line-height based algorithms* (Zeng and Binding, 2019).



Where for both OLCI and MERIS, λ1, λ2 and λ3 are centered at 681, 708, and 753 nm respectively.

* Daily Chla images are created and combined into rolling 14-day average (14d\_avg) Chla images.
* The algal bloom flag is raised on a pixel-by-pixel basis when Chla is in excess of 10 μg/L. *This threshold follows the World Health Organization guideline levels*, for relatively mild/low probabilities of adverse health effects, of 20,000 cells/mL (corresponding to 10 μg/L of Chla under conditions of cyanobacterial dominance).
* This threshold is also consistent with the approximate Chla above which most algorithms in the red-NIR are sensitive (Moses et al., 2009; Binding et al., 2013).
* With the same spectral and spatial resolution, the continuity in sensor specifications offered by MERIS and OLCI allow for consistent bloom retrievals for the period 2002–2011 and 2016 to present.
* There exists, however, a significant data gap over the years 2012–15 for which sensors with the required spectral configuration for the MCI are not available and *therefore indices for those years are not reported here*.

1. Algal Bloom Indices

All algal bloom indices are measured only on those pixels flagged as in bloom (i.e., Chla greater than 10 μg/L). Bloom statistics are extracted on a daily basis on both the 14d\_avg and daily composite images, as follows:

• **Bloom Intensity (μg/L)**: determined as the average Chla within the area flagged as in bloom.

• **Bloom Extent (km2 or % of lake area)** is measured as the total number of pixels flagged as in bloom. The number of bloom pixels multiplied by 0.09 (the 0.03 km × 0.03 km resolution of each pixel at nadir) gives the bloom extent in km2. Dividing the number of bloom pixels by the total number of lake pixels gives the extent as a % of lake area.

• **Bloom Severity (μg/L km2)** is determined as the product of Bloom Intensity and Extent, therefore representing the total surface Chla over the bloom area.

• **Bloom Duration** is calculated on a per pixel basis and mapped daily as a cumulative count from the start of the monitoring period (June 1st). Duration is linearly interpolated temporally between cloud-free dates; *for any given cloud-masked pixel the bloom is assumed present throughout the cloudy period* (and added to the cumulative bloom duration) if the bloom flag is raised on dates either side of the cloud period.

**• Annual Bloom Indices** are calculated as the average and maximum of daily indices (intensity, extent, severity) over the June to October monitoring season. The annual average bloom duration is extracted from the October 31st duration image as the average of all pixels greater than zero (representing an average bloom duration for the total area where a bloom was detected at least once over the bloom season).

3. Results

1. 3.1. Satellite data coverage and temporal binning

Data obtained was obtained at 300 X 300m.

However, partial swaths, cloud cover, lake-ice, and several quality masks reduce the frequency of useable data for any given pixel. Each pixel provided an average of 42, 36 and 44 cloud-free valid observations.

Challenges to accurately delineating and quantifying bloom spatial extent and intensity *is in dealing with loss of data over individual scenes*. Bloom statistics variability is primarily due to bias introduced by data gaps originating from cloud cover and/or quality flag masking, as well as spatio-temporal variations in surface bloom conditions brought about by advection, growth/senescence and wind driven mixing. Using a data coverage threshold to select useable images may be valuable; e.g say >70% valid data. However, the remaining 30% of any individual scene may mask the most intense portion of the bloom, leading to skewed bloom statistics.

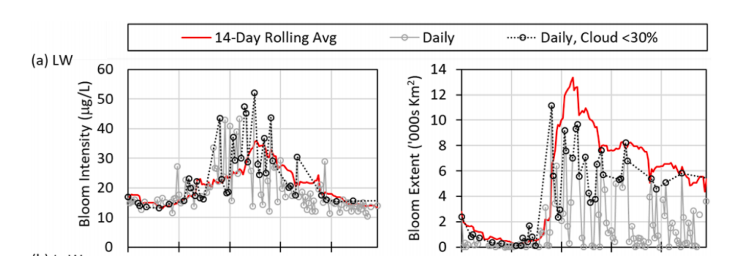
Conversely, an image with less than 70% valid data may adequately capture the maximum extent of a localized bloom. Hence even with 70% coverage imagery there is significant day-to-day variability in bloom intensity and extent brought about by data availability artifacts.

Furthermore, spatial coverage of daily imagery often has a seasonal bias; for example, on LoW, cloud-free images were more frequently captured in July and August. Using bloom indices derived from daily images would therefore require a priori knowledge of cloud cover and bloom location, a hindrance to the fully automated large scale monitoring potential that remote sensing offers. To address these data gaps and potential biases, the *adopted workflow produces rolling average composite Chla images*. To provide a product that offers consistency for the reduced data availability during the MERIS mission, we currently opt for a *14-day rolling average product* (14d\_avg), which results in near complete lake coverage. The 14d\_avg product adequately captures the maximum extent of the bloom without the day-to-day variability brought about by data gaps. *For bloom intensity*, while it is acknowledged a rolling average will smooth out peak Chla concentrations, *it also removes much of the* bias introduced by partial images and day-to-day variability from wind mixing events, therefore providing a consistent measure for trend detection.

*Wind-induced water column mixing* can prevent the bloom from rising to the surface, resulting in potential underestimation of bloom intensity from satellites (Wynne et al., 2010; Kutser et al., 2008). Binding et al. (2018) showed the close agreement between daily lake-average surface Chla and wind speed in LW, suggesting that day-to-day variability in surface Chla seen by the satellite is driven primarily by the repeated mixing and resurfacing of algal material in response to intermittent periods of wind mixing. In LE, the early season high in bloom intensity (Fig. 5c) is driven by an isolated bloom in Sandusky Bay, a protected bay on the southern shore of Lake Erie (Davis et al., 2015). This is a small localized but intense bloom, with spatial extent limited to the Bay itself (an area approximately 143 km2 ). It is likely more protected from the wind, which, combined with differences in bloom community composition (Rinta-Kanto and Wilhelm, 2006; Davis et al., 2015; Binding et al., 2019) results in bloom intensity showing little dependence on wind mixing (and so much less daily variability) compared with the exposed open lake bloom of later in the summer.

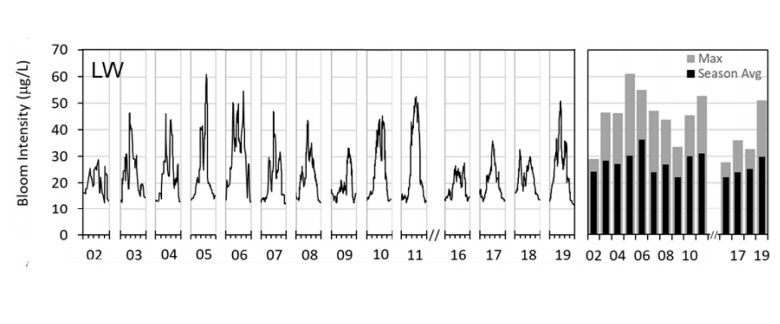
1. 3.2. Bloom indices
2. 3.2.1. Bloom spatial extent

Fig below presents the seasonal progression of bloom spatial extent for the years 2002–11 and 2016–19.



3.2.2. Bloom intensity

The highest season-average intensity, however, was observed in 2006 due to the more prolonged bloom that year.



Annual bloom severity index (ABSSI)

In order to account for variability in bloom intensity, spatial extent and duration, an annual bloom severity index (ABSI) is derived according to Eq. (4*), as the product of daily bloom intensity and extent averaged for the number of observations over the bloom season, n, from June 1st to October 31st*.

By taking the *average severity over the whole bloom season*, the index implicitly accounts for the bloom duration, providing a single combined measure of annual bloom conditions.

The bloom severity index could be further normalized by lake area or volume for inter-lake comparisons.

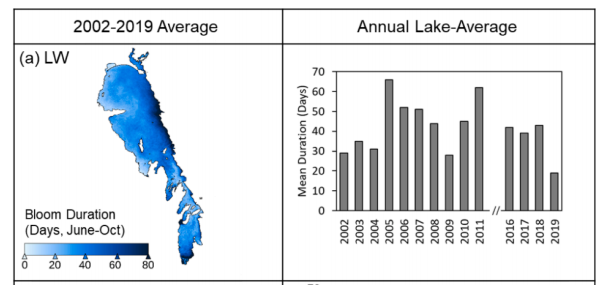


The ABSI can be used to show an overall spatial comparison on the bloom severity over the years.

**Discussion**

*4.1. Water quality management implications*

Sparse, fragmented datasets and inconsistencies in the timing and location of ground-based monitoring surveys of HAB events are major impediments to resolving spatial and temporal trends and developing robust management strategies for their mitigation.



**EDIT FROM HERE**

Satellite remote sensing has provided the means by which algal blooms can be observed.

with unprecedented frequency and spatial coverage. EOLakeWatch products go a long way to address existing spatial and temporal limitations in ground based monitoring capabilities, delivering frequent, large-scale synoptic observations of lake-wide algal bloom conditions. Mapped bloom products allow for the identification of areas of potential concern, enabling efficiencies in the allocation of field sampling resources and targeted remedial action in areas at higher risk of negative environmental, health or economic impacts. There is both documented and anecdotal evidence of changes in bloom phenology with warming lake temperatures (Vadadi-Fülop ¨ and Hufnagel, 2014; Palmer et al., 2015). Knowledge of the timing of peak bloom severity therefore offers additional improvements in the efficacy of in-lake bloom monitoring programs; existing annual surveys risk capturing peak bloom conditions some years but not others, and as such introducing significant uncertainty in temporal trend assessments from in situ datasets. The frequency of monitoring products afforded by EO therefore allow for robust objective inter-annual and inter-lake comparisons of bloom conditions. Delivery of near-real-time decision-ready information on bloom conditions to stakeholders provides opportunities to mitigate potential detrimental impacts to recreational and drinking waters. Image products can also be integrated into hydro-ecological models to deliver both short-term (Wynne et al., 2013; Soontiens et al., 2019) and seasonal (Stumpf et al., 2016a) algal bloom forecasting capabilities. Although cyanobacterial concentrations are often positively correlated with microcystins (Paerl and Otten, 2013), the same measure of bloom severity on each lake may not necessarily translate to a comparable risk of bloom toxicity due to seasonal and between-lake variability in phytoplankton community composition and toxigenicity. On Lake Winnipeg, microcystin concentrations in offshore blooms are typically well below recreational and drinking water quality guidelines (L´evesque and Page, 2011). Widespread blooms across southern waters of LoW typically dominated by Aphanizomenon flos-aquae have recorded consistently low microcystin concentrations (Watson and Kling, 2017; Zastepa et al., 2017). In contrast, blooms on Lake Erie have been shown to carry significant recurring risk of toxicity with Microcystis and Planktothrix considered the main toxin producers on the lake (RintaKanto and Wilhelm, 2006; Rinta-Kantoa et al., 2009; Steffen et al., 2014). Cyanobacterial toxins cannot be directly measured by remote sensing due to the lack of any discernible optical signature, and therefore any potential for bloom toxicity determination from space would rely upon proxy-based approaches (Stumpf et al., 2016b). Nevertheless, the combination of bloom indices presented here can help guide the spatial and temporal prioritization of sampling to determine the risk of bloom toxicity. Of note is the fact the date of peak bloom intensity does not necessarily coincide with the date of peak bloom extent, which may have implications for determining the timing of potential toxicity risk. HABs serve as key indicators of a lake’s response to anthropogenic eutrophication, while often also responding to a suite of other watershed, climate, and in-lake drivers (Dale and Beyeler, 2001; Clark et al., 2017). Although cyanobacterial blooms are fundamentally promoted by nutrient loading, climate plays a large role in the spatio-temporal dynamics of blooms in these lakes (Michalak et al., 2013; Watson et al., 2016; Binding et al., 2018), influencing the timing and concentrations of nutrient loads, lake ice cover, frequency and intensity of storm events, water temperature, stratification and mixing. Numerous studies have shown that Lake Erie blooms correlate well with spring P loads from the Maumee River (Stumpf et al., 2012; Michalak et al., 2013; Stow et al., 2015; Ho and Michalak, 2017), allowing for reasonably robust seasonal predictions of bloom severity (Stumpf et al., 2016a). However, Binding et al. (2018) showed that the response of Lake Winnipeg blooms to annual nutrient loads is confounded by meteorological conditions (wind mixing and summer lake temperature). Similarly, on Lake of the Woods bloom drivers are complicated by the internal loading of legacy nutrients which often obscures annual external load responses. Further understanding bloom dynamics and the processes driving their onset and progression, relies upon the accurate characterization of bloom conditions. Bertani et al. (2017) assessed the coherence of different approaches for algal bloom monitoring on Lake Erie and found that discrepancies in the characterization of seasonal and inter-annual bloom dynamics led to some inconsistencies in the relative importance of select environmental drivers of bloom severity. Variance among the derived bloom indices is shown here to be significant (i.e. the most extensive bloom was not necessarily the longest or most intensive), demonstrating the need for indices to be used in combination or for a single bloom indicator to capture the effects of variable bloom duration, extent and intensity. Collectively, the bloom indices presented here deliver a thorough assessment of bloom conditions, providing consistent, objective metrics with which to carry out analyses of bloom drivers. Satellite earth observations of blooms have been integral in determining phosphorus load targets required to reduce cyanobacteria blooms on Lake Erie (Stumpf et al., 2016a; Baker et al., 2019). EOLakeWatch products have also been integral in the development and validation of coupled hydrodynamic-ecosystem models used in scenariobased modeling to support ECCC’s LoW nutrient target setting (Valipour et al., 2020). The remote sensing indices reported here now provide a comprehensive suite of algal bloom metrics for monitoring the effectiveness of implemented nutrient management practices and guiding adaptive management frameworks across multiple watersheds. The science and end-user products delivered through EOLakeWatch directly support the Government of Canada’s water-resource management mandate and contribute to binational and intergovernmental agreements such as the Canada-Ontario Agreement on Great Lakes Quality and Ecosystem Health, Great Lakes Water Quality Agreement (GLWQA), and Canada–Manitoba Memorandum of Understanding Respecting Lake Winnipeg and the Lake Winnipeg Basin (ECCC, 2018). The Canadian Environmental Sustainability Indicators (CESI) program provides data and information on key environmental issues, including water quality, and is the prime instrument to track Canada’s progress on the Federal Sustainable Development Strategy (ECCC, 2013). Adoption of a reliable remote sensing algal bloom indicator and associated target connected to ecosystem management goals would go a long way to addressing the existing scarcity of in situ HAB indicators.

**Product consistency, uncertainties and limitation.**

A central requirement for a robust ecological indicator is a consistent and continuous time series of observations. It would be beneficial, therefore, to fill the data gap over the years 2012–15 between the MERIS and OLCI missions in order to more reliably determine temporal trends and lake responses to anthropogenic and environmental drivers. Equivalent algal bloom indices derived from NASA’s Moderate Resolution Imaging Spectroradiometer (MODIS), which has neither the same spatial resolution nor the same spectral band properties, are feasible, but require significant validation efforts to ensure continuity in bloom reporting. Moving forward, EO satellite missions are entering a phase of unprecedented data availability; with the launch of the sentinel-3B in 2018 (and future launch of 3C and 3D), the added coverage provided by a constellation of identical sensors will provide exceptional observation capabilities. Furthermore, additional imagery from the Sentinel-2 MultiSpectral Instrument (MSI), with spatial resolution of 10–30 m, has the potential to enhance monitoring of small, localized bloom events and nearshore processes. A benefit of the MCI algorithm as the basis of EOLakeWatch products is the availability of those required wavebands on the MSI allowing the retrieval of consistent chlorophyll and bloom products from this higher resolution imagery. However, the considerable variance documented in bloom indices extracted from daily imagery, brought about by both cloud-induced data gaps and the natural dynamic nature of blooms, highlights the need for frequent observations in order to reliably document any seasonal and long-term trends. We advise caution, therefore, in interpreting time-series observations using satellites such as Landsat and Sentinel-2 MSI with considerably reduced revisit times of 16 and 10 days respectively (Ho et al., 2017; Feng et al., 2020). While offering clear advantages of increased spatial resolution, reduced image frequency may risk misclassifying bloom severity compared with near daily observations offered by OLCI. There are several sources of potential uncertainty in the satellite retrievals presented, which should be considered when interpreting the derived bloom indices. The threshold for when increased algal biomass constitutes a bloom has been long-debated. While the guideline level of 20,000 cyanobacterial cells per ml (corresponding to 10 μg/L of Chla) set by the World Health Organization (Falconer et al., 1999) is often adopted, variation in this threshold used for defining the bloom on a pixel by pixel basis will clearly have significant impact on derived bloom statistics. For example, the LE bloom extent determined here is in agreement with that of Stumpf et al. (2012) which also reported the peak bloom extent of 2011 to be in excess of 5000 km2 using the MERIS Cyanobacteria Index (CI). The nominal threshold of the CI equivalent to 20,000 cells/mL (Davis et al., 2019) is consistent with that used here. In contrast, Sayers et al. (2019a) reported substantially lower LE algal bloom extent, which can be explained by the different threshold of Chla (concentrations greater than 18 μg/L) they adopted to define bloom conditions. Furthermore, it’s acknowledged that use of a rolling average product will reduce the detection of extremes in bloom indices and high frequency variability. For example, peak bloom extent reported here for LW was on average 18% lower than shown in Binding et al. (2018) for the 2002–2011 period, due to the fact our previous study analysed only whole-lake cloud-free daily images rather than the continuous 14-day rolling averages used here. As additional data sources are included in the processing stream (e.g. Sentinel 3-B OLCI and successors), the minimum number of days required to generate a composite image with complete lake-wide coverage will decrease, thus enabling better detection of real high-frequency bloom variability while minimizing cloud related artifacts. Satellite coverage is considerably greater than is afforded by ground sampling alone but image frequency will undoubtedly result in some bloom occurrences being missed during periods of prolonged cloud cover, a limitation that can be alleviated by integrating image products with statistical (Obenour et al., 2014) or physical (Soontiens et al., 2019) models. The relationship between Chla and MCI (Eq. (3)) was first developed for LoW (Binding et al., 2011) and has been shown to be broadly consistent for all three lakes (Binding et al., 2018, 2019). Nevertheless, one of the largest sources of uncertainty in the relationship between Chla and satellite-measured MCI is the variability of local inherent optical properties (IOPs) of the dissolved and particulate materials that contribute to the remote sensing reflectance signal. Cyanobacteria blooms often exhibit unique backscatter and absorption features due to the presence of gas vacuoles (Matthews and Bernard, 2013), colonial aggregation (Paerl and Ustach, 1982), or variable pigmentation (Stomp et al., 2007). As such, diversity in phytoplankton community compositions can result in highly variable optical properties as reported in Lake Erie (Binding et al., 2008; O’Donnell et al., 2010; Moore et al., 2017; Sayers et al., 2019b) with significant impact on chlorophyll retrieval algorithms (Binding et al., 2019). Such variability in IOPs may introduce seasonal and/or between-lake bias in derived chlorophyll. Furthermore, the Chl-MCI relationship is known to move towards saturation at Chla ~ 300 μg/L (Binding et al., 2013; Zeng and Binding, 2019), therefore products derived from a linear algorithm may underestimate Chla at extremely high concentrations. Advances in retrieval algorithms brought about by optical water type classifications (Neil et al., 2019), machine-learning (Pahlevan et al., 2020), or hyperspectral imaging (Giardino et al., 2019) provide promise in reducing the uncertainty in derived chlorophyll concentrations moving forward.

Conclusions & future directions

Products emanating from EOLakeWatch have advanced significantly Canadian inland water algal bloom monitoring capabilities, making fit-for-purpose end-user products accessible to a wide range of stakeholders in support of lake water quality management. Collectively, the suite of satellite-derived indices developed for three turbid eutrophic lakes, provide objective and consistent measures of bloom conditions that are vital for comprehensive algal bloom monitoring and research. Such products have been integral in providing near-real-time observations of bloom conditions, identifying areas of potential concern, documenting spatio-temporal trends, improving understanding of environmental drivers of blooms, as well as guiding, and monitoring the effectiveness of, nutrient management actions. Future advancement of EOLakeWatch operations, including the expansion of geographic coverage and delivery of an enhanced suite of EO-derived water quality products, promises to augment further opportunities for the integration of EO technologies into Canadian federal solutions for national water quality monitoring, science, and management. Such expansion would enable more comprehensive and more cost-effective large-scale water quality monitoring across Canada. In some regions, EO may be an invaluable complement to in situ monitoring programs, providing synoptic views not possible with ground-based observations, while for large swaths of Canadian inland and coastal waters, particularly northern and remote communities, it may be the only monitoring solution. With anecdotal evidence of increasing bloom occurrences in isolated previously pristine waterbodies and northern lakes, reliable remote sensing observations of HAB events may prove invaluable in documenting current, and modeling future, impacts of climate change on Canada’s inland water ecosystems.

1. **Hourly remote sensing monitoring of harmful algal blooms (HABs) in Taihu Lake based on GOCI Images – Nice intro**

The linear mixing model (LMM) and the normalized difference vegetation index (NDVI) threshold method are combined to extract the HAB area from GOCI images with 500-m spatial resolution.

The results show that when the NDVI threshold is 0.1, the area error of HABs is the smallest when the extracted HAB pixels mask the decomposition results of mixed pixels. Compared with the NDVI threshold method and LMM method, the inversion accuracy is greatly improved, and the accuracy is stable in different regions. It can provide technical support for the decision-making and assessment of HAB ecological disasters.

**Method**

1. **NDVI**

Since the spectral characteristics of the HABs are similar to those of vegetation, the information of HABs can be extracted effectively according to NDVI (Oyama et al. 2015; Shi et al. 2019). NDVI is defined as the normalized ratio of the red band and the near-infrared band (Norris and Walker 2020), i.e.:

NDVI = …………………...(i)

Where:

NIR and Red represent the reflectance of the near-infrared band and red band, respectively for the Landsat8 OLI image, they represent the reflectance of band 5 (865 nm) and band 4 (655 nm), respectively According to the band settings of Landsat8 OLI, the information of HABs is extracted by the threshold method using the NDVI model, and the discriminant equation is as follows:

NDVI > NDVIt …………………...(ii)

In Eq. 2, NDVIt represents the threshold value of NDVI. To ensure the accuracy of the HABs, the threshold value is determined by human–computer interaction. When the NDVI value is greater than the threshold value, the pixels are considered as HAB pixels.

1. **LMM method**

As a method of mixed pixel decomposition, it the reflectance of a pixel in a certain band is a linear combination of the endmember (pixel containing only one kind of feature information) reflectance of the component pixel with the proportion of its pixel area as the weight coefficient (Lyit and Genc 2011).

The mathematical expression of LMM was expressed as follows (Kim et al. 2020; Meng et al. 2007):



Where:

Riλ is the reflectance of the i-th pixel in the λ band (known);

fki is the ratio (to be determined) of the area of the k

LMM separates Riλ from the mixed pixels and extracts the average reflectance Ckλ of each endmember. By solving the linear equation, the area ratio fki of the endmember in the pixel is inversely solved, so that all the pixels are decomposed into the components of these basic components.

1. **Pure pixel selection**

The pixels in the whole lake area can be simplified into three regions:

* Pure water body pixels,
* Pure HAB pixels
* Mixed pixels of water and HABs.

The specific methods for the selection of the two types of pure pixels are as follows: The HAB area is selected by visual judgment, and the pixel with the highest NDVI value is selected as the HAB pixel; in the lake area, the pixel with the lowest DN value or the sum of reflectance values is selected as the pure water pixel (10 minimum pixels can be selected for the average in specific operation)

# GIS LONGUE WEBSITE: Monitoring Algal Blooms with Remote Sensing

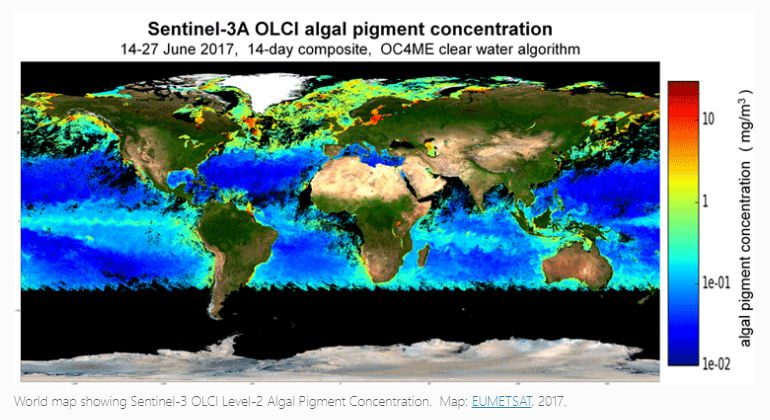
<https://www.gislounge.com/monitoring-algal-blooms-remote-sensing/>

Algal blooms present a major problem, as they are often instigated by pollution and changing temperature and can kill a variety of marine and freshwater life through eutrophication. Usually, these blooms give a distinct coloration visible in imagery, such as the red tide, although the coloration does vary depending on the type of bloom.

Given the importance of knowing how these blooms affect aquatic life, remote sensing techniques using a variety of available imagery have been developed. The southern Benguela in South Africa is one rich area for fishing that algal blooms threaten. Variation in chlorophyll is one major variable in algal blooms in the area; using the [Sentinel-3](https://www.gislounge.com/learn-access-use-sentinel-3-data/) Ocean and Land Color Instrument (OLCI) system, this instrument has been designed to capture signatures of biogeochemical that affect algal bloom growth.

## **Using Remote Sensing to Distinguish Areas of High Algal Growth**

In low biomass areas, an adapted version of the OC4MEblue-green band-ratio algorithm can be used to distinguish high concentrations of algal growth, while a red-Near Infrared (NIR) band-ratio algorithm can be applied in high biomass areas. While algal blooms are often a seasonal event, thresholds within the algorithms could allow the tracking of events over time and space when more extreme events take place. This has the benefit of improving data collection for future assessments that attempt to forecast these blooms as well as knowing what areas are impacted.[[1]](https://www.gislounge.com/monitoring-algal-blooms-remote-sensing/" \l "_ftn1)



## **Detecting Chlorophyll-a With Remote Sensing**

Challenges in oceanic observations have been seen particularly in coastal environments, where band-ratios algorithms, which work best with sensors in open ocean water, are less accurate in coastal regions, particularly in the detection of chlorophyll a (Chl-a). This is why Sentinel-3’s OLCI system provides a major upgrade to scientific capabilities in detecting this important chemical that relates to major algal blooms. In particular**, improvements in red-NIR band ratio detection** have been a major reason for increased detection in coastal water for phytoplankton that have chlorophyll a.[[2]](https://www.gislounge.com/monitoring-algal-blooms-remote-sensing/" \l "_ftn2)

## **Differentiation of Algal Species in Inland Water Regions**

Other challenges identified in the monitoring of algal blooms using remote sensing data include viewing blooms in inland water regions, particularly in small bodies of water, and in highly turbid environments that block out easier views of algal growth. In fact, most papers in recent years have focused on inland regions, as open ocean areas have been seen to be better captured by low resolution systems such as MODIS and MERIS. Improvements in adjacency correction, inversion-based retrieval models and optical property measurements have, however, allowed advancements to be made in these inland areas in the last few years.[[3]](https://www.gislounge.com/monitoring-algal-blooms-remote-sensing/" \l "_ftn3)

Increased spatial and spectral range of hyperspectral sensors on airborne instruments, such as MASTER, HICO, and AVIRIS data, have also enabled better differentiation of algal species in smaller, inland bodies of water. One study in Pinto Lake California demonstrated that Aphanizomenon and Microcystis species could be separated using a **spectral shape algorithm**. Regular monitoring allows a better understanding of seasonal variations as rainfall conditions and surface water temperatures change.[[4]](https://www.gislounge.com/monitoring-algal-blooms-remote-sensing/" \l "_ftn4)

Given that algal blooms are best covered within different parts of the electromagnetic spectrum, seasonal variation, resolution, and other parametric factors, combining multiple imagery using spatial-temporal analysis and image merging and interpolation techniques to best estimate and determine algal bloom regions. Older systems, such as AVHRR and CZCS, are also available, while also providing historical data. Sea surface and water surface temperatures, along with Chl-a, have also been used to capture existing data and have shown a strong link to algal growth. Thus, systems that can integrate such key parameters and utilize multiple and historical data could, in the future, best predict how algal blooms may grow and affect different regions.[[5]](https://www.gislounge.com/monitoring-algal-blooms-remote-sensing/" \l "_ftn5)

## **References**

[[1]](https://www.gislounge.com/monitoring-algal-blooms-remote-sensing/" \l "_ftnref1) For more information on the use of Sentinel-3 OLCI for algal blooms, see:  <https://www.eumetsat.int/website/home/Images/ImageLibrary/DAT_3798232.html>.

[[2]](https://www.gislounge.com/monitoring-algal-blooms-remote-sensing/" \l "_ftnref2) For more on detection issues raised by remote sensing literature on algal blooms, see:  Blondeau-Patissier, D., Gower, J.F.R., Dekker, A.G., Phinn, S.R., et al. (2014) [A review of ocean color remote sensing methods and statistical techniques for the detection, mapping and analysis of phytoplankton blooms in coastal and open oceans.](https://www.sciencedirect.com/science/article/pii/S0079661114000020) Progress in Oceanography. [Online] 123, 123–144. Available from: doi:[10.1016/j.pocean.2013.12.008](https://doi.org/10.1016/j.pocean.2013.12.008).

[[3]](https://www.gislounge.com/monitoring-algal-blooms-remote-sensing/" \l "_ftnref3) For more on improvements in inland environments, see:  Palmer, S.C.J., Kutser, T. & Hunter, P.D. (2015) [Remote sensing of inland waters: Challenges, progress and future directions](https://www.sciencedirect.com/science/article/pii/S0034425714003666). Remote Sensing of Environment. [Online] 157, 1–8. Available from: doi:10.1016/j.rse.2014.09.021.

[[4]](https://www.gislounge.com/monitoring-algal-blooms-remote-sensing/" \l "_ftnref4) For more on the use of hyperspectral imagery, see:  Kudela, R.M., Palacios, S.L., Austerberry, D.C., Accorsi, E.K., et al. (2015) [Application of hyperspectral remote sensing to cyanobacterial blooms in inland waters](https://www.sciencedirect.com/science/article/pii/S0034425715000437). Remote Sensing of Environment. [Online] 167, 196–205. Available from: doi:10.1016/j.rse.2015.01.025.

[[5]](https://www.gislounge.com/monitoring-algal-blooms-remote-sensing/" \l "_ftnref5) For more on integrative systems approach to remote sensing of algal blooms, see:  Shen, L., Xu, H. & Guo, X. (2012) [Satellite Remote Sensing of Harmful Algal Blooms (HABs) and a Potential Synthesized Framework](http://www.mdpi.com/1424-8220/12/6/7778). Sensors. [Online] 12 (12), 7778–7803. Available from: doi:[10.3390/s120607778](https://doi.org/10.3390/s120607778).

## **See Also**

* [Ready for Summer – Remote Sensing of Bathing Water Quality](https://www.gislounge.com/ready-summer-remote-sensing-bathing-water-quality/)
* [Blooms and Scums in Lake Erie](https://www.geographyrealm.com/blooms-scums-lake-erie/)

1. **Harmful Algal Blooms Threaten the Health of Peri‑Urban Fisher Communities: A Case Study in Kisumu Bay, Lake Victoria, Kenya**

