Data indicators and parameters that will contribute to building a risk map for cyanoHABs

Overall conceptual framework:

- General detection of surface "bloom" with chlorophyll-a; CI-cyano more specific for cyanoHAB (see remote sensing overview from ITRC)
    - Spatial scale and complexity are major considerations in terms of potential remote sensing tools.
        - Sensors with larger pixel sizes for larger lakes and reservoirs (such as Sentinel 3)
        - Sensors with smaller pixel sizes for smaller lakes, rivers, and complex coastal areas
- Sub-surface blooms, picocyanobacteria, and benthic cyanobacteria are harder to detect than surface blooms with remote sensing of chl-a/CI-cyano but habitat availability, environmental conditions, and hydrodynamics may help predict.
- Hydrodynamic and climate event indicators may signal potential conditions for "bloom" such as nutrient input from freshwater or anomalous change in temperatures
- Environmental conditions can inform potential bloom initiation/growth
    - Longer residence time, lower flow, higher nutrients, and increased temperature associated with many planktonic blooms, such as Microcystis
    - Some cyanobacteria occur in lower nutrient, relatively higher flow, lower residence time. For example, more oligotrophic lakes may have sub-surface blooms (Fournier *et al.*, 2021), benthic cyanobacteria (Vadeboncoeur *et al.*, 2021), and/or picocyanobacterial (Callieri *et al.*, 2022) that may not be apparent with standard surface monitoring methods

Potential Process for CyanoHABs

- Use imagery (color and multi/hyperspectral) and chlorophyll-a to detect potential surface or near surface bloom and distinguish if cyanobacterial bloom
    - Spatial scale and complexity are major considerations in terms of potential remote sensing tools.
        - Sensors with larger pixel sizes for larger lakes and reservoirs (such as Sentinel 3)
        - Sensors with smaller pixel sizes for smaller lakes, narrow reservoirs, rivers, and complex coastal areas (such as Sentinel 2, Landsat, etc.)
        - Sub-surface blooms, picocyanobacteria, and benthic cyanobacteria are harder to detect than surface blooms with remote sensing of chl-a/CI-cyano but habitat availability, environmental conditions, and hydrodynamics may help predict.
- If potential cyanobacterial bloom identified:
    - If hyperspectral imagery available, may be able to distinguish cyanobacteria type

    - Consider habitat type (waterbody size, mixing, and nutrient status) and water temperatures
        - See (Chorus and Welker, 2021) Table 4.4 for overview of 7 planktonic cyanobacterial functional groups based on habitat type (waterbody size, mixing, and nutrient status) and water temperature; note potential microcystin production common across functional groups
    - consider transport to nearby areas with current, wind
- If no potential cyanobacterial bloom identified, but significant change in water temperature, stratification or nutrient input event detected,
    - consider subsequent changes in water temperature, stratification, flow, or wind to consider potential for new bloom or movement of sub-surface bloom to surface
- consider climate variations (and related shift in environmental conditions) as factor in extent or severity of events

Overview of cyanoHABs

- Include water column/planktonic HABs (surface and sub-surface) and benthic cyanobacteria
    - Some planktonic and benthic cyanobacteria grow in brackish waters or cells (with intracellular toxins) may be transported into coastal areas
    - Some benthic cyanobacteria species grow in marine waters, such as coral reefs and shallow atolls
        - Diverse cyanobacteria genera in benthic cyanobacteria mats collected from 6 remote South Pacific Islands (Biessy *et al.*, 2021)
        - Benthic cyanobacteria on coral reefs, Brazil (Ribeiro *et al.*, 2022)
- (Chorus and Welker, 2021): Among the hydrophysical conditions affecting cyanobacterial occurrence, the most important ones are turbidity, temperature profiles (stratification), pH, oxygen concentration and – for rivers or streams – flow rate
    - See Table 4.4 for overview of 7 planktonic cyanobacterial functional groups based on habitat type (waterbody size, mixing, and nutrient status) and water temperature; note all groups include potential microcystin producers, other toxin classes
        - Shallow, turbid mixed layers with 20-27.5 °C
        - Warm, mixed layers with 29-35 °C
        - Shallow lakes or eplimnion of deep layers, eutrophic
        - Oligotrophic to eutrophic, shallow to deep with 27-39 °C
        - Oligotrophic to eutrophic, shallow to deep with 28-34 °C
        - Small eutrophic intermittent mixing 20-29 °C
        - Mesotrophic metalimnion with 15-23 °C
- Global review for Microcystis (Harke *et al.*, 2016)

- Can overwinter in benthos
- Blooms generally with water temperature above 15 °C
- Occurrence in all continents except Antarctica

- Predictive models for cyano blooms (Rousso *et al.*, 2020).
  - Water temperature (+), water transparency (Secchi depth, -), and nutrients (phosphorous in water or sediment, water column nitrate) as consistent predictors for freshwater cyanobacterial blooms
  - Water circulation patterns also a factor.
- Predictions for cyano in rivers, South Korea (Kim *et al.*, 2020)
  - Water temperature, velocity, phosphorous
- Stratified lakes can have sub-surface blooms of cyanobacteria such as *Planktothrix* (Fournier *et al.*, 2021) that may appear suddenly at the surface when lake turnover occurs.
- Picocyanobacteria may not be detected by standard monitoring methods due to filter size or microscopic magnification as well as distribution within the water column.

Multi/Hyperspectral imagery

- Overall review of remote sensing for algal blooms in lakes (Rolim *et al.*, 2023)

From: Remote sensing for mapping algal blooms in freshwater lakes: a review

Satellite	Sensor	Spatial resolution	Spectral resolution	Temporal resolution	Data availability period	References
Landsat-8	Operational Land Imager (OLI)	30 m	11 + pan	16 days	2013–present	Alarcon et al. (2018)
AQUA (EOS PM-1)/TERRA (EOS AM-1)	Moderate Resolution Imaging Spectroradiometer (MODIS)	250 m–1 km	13	Daily	1999/2002–present	Avouris and Ortiz (2019)
Sentinel-2A,2B	Multispectral Instrument (MSI)	10 m–60 m	9	5 days	2015/2017–present	Cao et al. (2021); Lobo et al. (2021)
Sentinel-3A/3B/3C	Ocean and Land Color Instrument (OLCI); SLSTR (Sea and Land Surface Temperature Radiometer); SRAL (SAR Altimeter); DORIS (Doppler Orbitography and Radiopositioning Integrated by Satellite); MWR (Microwave Radiometer)	300 m	17	5 days	2016/2018–present	Ogashawara (2019)
Dubaisat-1	DubaiSat-1 Medium Aperture Camera (DMAC)	5 m	4 + pan	3–5 days	2009–present	Ali et al. (2013)
Dubaisat-2	High Resolution Advanced Imaging System (HiRAIS)	4 m	4 + pan	8 days	2013–present	Ben-Romdhane et al. (2018)
WorldVew-2	Multispectral Sensor (MSS)	1.84 m	8 + pan	1.1–3.7 days	2009–present	Gray et al. (2021)
WorldVew-3	MSS, CAVIS, and SWIR sensors	1.24–3.2	8 + pan + 12 CAVIS bands	< 1 day	2014–present	Gray et al. (2021)
GaoFen-1	Active Pixel Sensor (APS) star sensor	3.2 m	4	5 days	2014–present	Hang et al. (2022)
RapidEye	Multispectral Imager (MSI)	5 m	5	1 day	2008–present	Mishra et al. (2019)
PlanetScope	Dove-C, Dove-R, SuperDove	3 m	4 (Dove)/8 (SuperDove)	1 day	2016–present	Niroumond-Jadidi and Bovolo (2021)
PRISMA	HYC (Hyperspectral Camera) module and the PAN (Panchromatic Camera) module	30 m; 5 m in panchromatic	239 bands in visible, infrared, and shortwave infrared spectra	29 days	2019–present	O'Shea et al. (2021)

- Bio-optical properties of 10 cyanobactera, laboratory cultures (Wojtasiewicz and Stoń-Egiert, 2016)
  - (*A. flos-aquae* KAC 15, *M. aeruginosa* CCNP 1101, *Anabaena* sp. CCNP 1406, *S. salina* CCNP 1104, *Phormidium* sp. CCNP 1317, *N. spumigena* CCNP 1401, *Synechococcus* sp. CCNP 1108, *Nostoc* sp. CCNP 1411, *Cyanobacterium* sp. CCNP 1105, *Pseudanabaena cf. galeata* CCNP 1312)
  - Absorption at 440, 630, 675, and ratio of 440 to 675 (Table 2)

- Light scattering and attenuation properties (Table 3)

surface/near surface planktonic blooms on larger water bodies

- HY-1C UV
    - Lake Taihu, China (Suo *et al.*, 2022): UV reflection characteristics of cyanobacteria, which are interpreted by the *in-situ* measured reflectance spectra at the Taihu Laboratory for Lake Ecosystem Research (TLLER, Fig. 1c inset). The second is the UV characteristics of floating cyanobacteria in spaceborne UV images. The UV data at 355 and 385 nm were provided by the Ultraviolet Imager (UVI) onboard Haiyang-1C (HY-1C).
- NASA MODIS
    - Lake Taihu, China (Jia, Zhang and Dong, 2019):
        - FAI gradient histogram statistics of long-term (2000 to 2008) MODIS data, Hu et al. determined FAI > −0.004 as the floating cyanobacteria distinguishing threshold. FAI is not sensitive enough to distinguish between cyanobacteria and macrophyte, so our obtained cyanobacteria bloom spatiotemporal patterns were contaminated by macrophytes more or less, especially in East Lake and Gong Bay. Compared to Landsat TM/ETM+/OLI images for validation
- Sentinel 3 OLCI
    - Large lakes and reservoirs, India (Maniyar, Kumar and Mishra, 2022): CyanoKhoj can be made more robust by integrating data from multiple sensors such as Landsat or MODIS derived temperature products, and also high-resolution Sentinel 2 data for a cross-calibrated model, which can be more robust in terms of the detection and quantification of CCD and PC

Subsurface bloom in deep reservoirs

- Daechung Reservoir (Kwon *et al.*, 2020): develop an improved bio-optical remote-sensing method using in-situ remote-sensing reflectance (Rrs) at different water depths and cumulative PC and Chlorophyll-a (Chl-a) concentrations, which was cumulated from the surface to a 5-m water depth
    - Dominant cyanobacteria genus Anabaena, Microcystis, Oscillatoria in early summer to late autumn
    - Laboratory pigment analyses and in situ remote sensing reflectance with field spectroradiometer
    - Hyperspectral images were collected using a Nano-Hyperspec® hyperspectral imaging sensor (Headwall Photonics Inc., MA, US) installed on a MATRICE M600 Pro hexacopter (DJI Inc. China)
    - Band-ratio algorithm

surface/near surface planktonic blooms with smaller water bodies and coastal regions

- Multiple hyperspectral sources, Pinto Lake, USA (Kudela *et al.*, 2015):
- MODIS aqua/terra, Baltic Sea (Karlson *et al.*, 2022) – Aphanizomenon, Dolichospermum, and Nodularia
    - Moderate Resolution Imaging Spectroradiometer (MODIS) (Masuoka et al., 1998) on the NASA-satellites Aqua and Terra for the years 2002–2020. Level 2 data were downloaded from NASA's OceanColor Web https://oceancolor.gsfc.nasa.gov and processed using

PyTROLL software available open source at https://pytroll.github.io/. Data was masked, and bad data removed, using the standard quality flags ATMFAIL, LAND, HIGLINT, HILT, HISATZEN, STRAYLIGHT, CLDICE, HISOLZEN, LOWLW, CHLFAIL, MAXAERITER, ATMWARN (https://oceancolor.gsfc.nasa.gov/atbd/ocl2flags/). High resolution data 250x250 m

  - Excluded areas with water depth <10 m generally and <30 m in known highly turbid regions
  - Surface accumulations of cyanobacteria were defined as when ocean colour band 13 (part of the red spectra) with a centre wavelength at 667 nm exceeded or was equivalent to 0.0012 sr^{-1}. Inconsistency with water samples collected 0-10 m with microscopic ID.
  - In addition to the detection from band 13, band 12 (centre wavelength: 555 nm) was used in order to detect cyanobacterial sub-surface accumulations, as light from this wavelength penetrates deeper into the water column compared to band 13. A threshold of 0.00435 sr^{-1} was used.
- Landsat and Sentinel-2
  - Multiple locations (Niroumand-Jadidi and Bovolo, 2023): advanced deep-learning-based model called Deep OrAnge Band Learning Network (DOABLE-Net) for retrieving a virtual orange band from multispectral bands of Landsat-8/9 or Sentinel-2. The Pan-based orange band retrieval technique provided promising results in mapping phycocyanin concentration in Lake Erie [16] and Eagle Creek Reservoir [17] and has been implemented in the ACOLITE processor [18].
- Sentinel 2
  - Irongate and Copco Reservoirs, Klamath River, USA (Kislik *et al.*, 2022): used for chl-a detection of blooms
  - Inland waters, Latin America (Lobo *et al.*, 2021): used for chl-a detection of blooms
- LandSat vs ground-based hyperspectral reflectance; Oklahoma lakes (Cook *et al.*, 2023): we compared reflectance-algal pigment models using Landsat satellite data and ground-based hyperspectral reflectance. We built empirical models relating satellite spectral reflectance to chlorophyll-*a* and phycocyanin
- DESIS hyperspectral (Legleiter *et al.*, 2022): Hyperspectral data used to identify chl-a, CI, and predicted cyanobacterial genera
  - DESIS from ISS
  - NDWI, NDCI, and CI (see Table 2)

Table 2
Spectral indices used to identify waterbodies and quantify the amount of chlorophyll-*a* and cyanobacteria present therein. $R_{rs}(\lambda)$ denotes the remote sensing reflectance for the DESIS band centered at wavelength λ in units of nm.

Index	Equation	Source
Normalized difference water index (NDWI)	$\frac{R_{rs}(560.6) - R_{rs}(865.4)}{R_{rs}(560.6) + R_{rs}(865.4)}$	(McFeeters, 1996)
Normalized difference chlorophyll index (NDCI)	$\frac{R_{rs}(706.7) - R_{rs}(665.3)}{R_{rs}(706.7) + R_{rs}(665.3)}$	(Mishra and Mishra, 2012)
Cyanobacterial index (CI)	$-R_{rs}(680.9) - R_{rs}(662.8) - [R_{rs}(709.4) - R_{rs}(662.8)]\frac{680.9 - 662.8}{709.4 - 662.8}$	(Wynne et al., 2008)

  -

- SMASH workflow with spectral mixing technique using existing spectral library consisting of 12 cyanobacterial genera

- Landsat 8; Italian coast (Teta *et al.*, 2017):
    - Landsat 8 (30 m pixel size) and aircraft imagery (10-15 cm pixel size)
    - NDVI algorithm used to detect cyanoHAB based on higher resolution aerial imagery but overall chlorophyll-a for lower resolution Landsat 8
- Pigment ratios to distinguish 4 cyanobacteria orders (orders: Synechococcales, Chroococcales, Oscillatoriales and Nostocales) (Bonilla *et al.*, 2023b)
- ALI, Hyperion, Hymap; Great Barrier Reef, Australia (Kutser, Dekker and Skirving, 2003)
    - A spectral library of coral reef benthic communities was collected from the Great Barrier Reef. Hydrolight 4.1 was used to simulate remote sensing reflectances.
    - One multispectral and two hyperspectral sensors were simulated: the Advanced Land Imager (ALI, space borne; 30 m resolution), Hyperion (space borne; 30 m resolution), and HyMap (airborne, at 1.5 km altitude, 3 m variable resolution).

Table 1. Technical characteristics of remote sensing sensors used in model simulations.

Sensor	Spectral Resolution (FWHM)	Spatial resolution	SNR	Spectral range	Number of spectral bands
Hyperion	10 nm	30 m	160 : 1	350–2,400 nm	240
Hymap	15 nm	3 m (variable)	1000 : 1	440–2,480	126
ALI	60 nm	30 m	250 : 1	430–2,440	10

    - Distinguish to water depth of 5-6 m
    - Pixel size of current sensors results in most pixels containing multiple substrate types
- AERONET-OC, Baltic Sea (Cazzaniga, Zibordi and Mélin, 2023)
    - High CDOM and recurring cyanoHABs with picocyanobacterial Synechococcus, Nodularia, Aphanizomenon, and Dolichospermum including accumulations 10 m below the surface
    - Compare with OLCI and MODIS ocean color products

Table 1. Band combinations analysed in this study using both AERONET-OC and OLCI or MODIS $R_{RS}(\lambda)$ data.

Band combination	Reference
$R_{RS}(442)$-$R_{RS}(412)$	(Karabashev, 2021)
$R_{RS}(560)$-$R_{RS}(510)$	(Dash et al., 2011)
$R_{RS}(620)/R_{RS}(665)$	(Schalles and Yacobi, 2000; Woźniak et al., 2016)
$R_{RS}(560)+\frac{620-560}{665-560}*(R_{RS}(665)-R_{RS}(560))-R_{RS}(620)$	(Qi et al., 2014)
$R_{RS}(667)$ (turbid water flag)	(Kahru et al., 2007; Kahru and Elmgren, 2014)
$R_{RS}(443)/R_{RS}(560)$, $R_{RS}(490)/R_{RS}(560)$, $R_{RS}(510)/R_{RS}(560)$	OC4ME *Chl-a* algorithm for OLCI bands (Morel et al., 2007)
$R_{RS}(443)/R_{RS}(547)$, $R_{RS}(488)/R_{RS}(547)$	OC3M *Chl-a* algorithm for MODIS bands (O'Reilly et al., 1998)
$R_{RS}(560)/R_{RS}(490)$, $R_{RS}(620)/R_{RS}(490)$, $R_{RS}(665)/R_{RS}(510)$, $R_{RS}(560)$-$R_{RS}(490)$, $R_{RS}(560)$-$R_{RS}(620)$, $R_{RS}(560)$-$R_{RS}(665)$	From this study for OLCI bands
$R_{RS}(547)/R_{RS}(488)$, $R_{RS}(667)/R_{RS}(531)$, $R_{RS}(547)$-$R_{RS}(488)$, $R_{RS}(547)$-$R_{RS}(667)$	From this study for MODIS bands

Benthic cyanobacteria in flowing systems

- Buffalo River, USA (Legleiter and Hodges, 2022):
  - Eight-band images with 2 m and 1.81 m pixels were acquired by the WorldView3 satellite. Cloud-free, four-band, 0.5 m pixel images from SkySat with addition of the image-derived depth estimates obtained via OBRA as a predictor variable, in addition to all of the spectral bands, for assigning pixels to algal density categories.
  - Overall, the results of this study suggested that, for the conditions observed along the Buffalo River at the time the images were acquired, mapping benthic algae from readily available remotely sensed data using established depth retrieval and image classification methods was more difficult than anticipated, but allows for repeated coverage of larger and/or more remote areas than feasible by field monitoring. Spectral band number was a greater limitation than spatial resolution.

Chlorophyll-a

- WHO recommendations for Chl *a* concentrations above 10 mg m^{-3}
- Not specific to cyanoHABs and may overestimate cyanobacterial abundance relative to other phytoplankton/algae

Coastal zones

- Sentinel 2; Río de la Plata estuary (South America) (Maciel *et al.*, 2023): Sentinel-2 Multispectral Instrument (S2-MSI) detection of cyanoHAB in highly turbid estuary
    - o For the study site, cyanobacteria represented 61% (median, from 0% to 100%) and 99% (median, from 63% to 100%) of the total phytoplankton biovolume for chl-a concentrations greater than 10 μg/L and 24 μg/L, respectively. Moreover, cyanobacteria were dominant (> 50% of the total biovolume) in 70% of the samples for which chl-a was above 10 μg/L, and were dominant in all samples that had chl-a greater than 24 μg/L.
    - o Chl-a indices with best fit: 3BI, NDCI, and SS(665). The SS index that had higher correlations with measured chl-a concentration was centred at the red band (665 nm), with the baseline between the green (560 nm) and red-edge bands (705 nm). To overcome the challenges imposed by the high variability of turbidity levels (mainly associated to inorganic suspended sediments) on chl-a retrievals, we proposed the simultaneous application of two algorithms, based on 3BI and -SS(665), to monitor chl-a threshold levels that are of interest for risk exposure when cyanobacteria dominate.
- Sentinel 2; Rio de la Plata estuary, Uruguay (Aubriot *et al.*, 2020): large cyanobacterial blooms composed of the *Microcystis* and *Dolichospermum*
    - o Sentinel-2 (ESA) MSI images were downloaded from the L1C level and atmospherically corrected with the Dark Fit Spectrum method. The earth and cloud pixels were masked, and NDCI was calculated with a fixed range using ACOLITE software (Vanhellemont and Ruddick, 2016).
    - o Sentinel 2 NDCI with values of NDCI >0.06 were considered for mapping the surface area of cyanobacterial blooms
    - o Identified likely upstream sources and transport of cyanobacterial biomass through river and reservoir system to the estuary
- MODIS, Florida estuary, USA (Cannizzaro *et al.*, 2019): detection of marine picocyanobacteria (*Synechococcus*) with chl-a with bloom (>5 mg m^{-3}) and non-bloom (<5 mg m^{-3})

surface/near surface planktonic blooms on larger water bodies

- Sentinel 3 OLCI; Lake Okochobee and St Lucie Estuary, FL USA (Reynolds *et al.*, 2023): Florida Department of Environmental Protection (FDEP) uses chlorophyll-*a* concentration as an indicator for cyanoHABs within Lake Okeechobee, designating that bloom-forming algae are considered a bloom at chlorophyll-*a* concentrations above 40 µg/L (Havens et al., 1994). The conversion we used to estimate chlorophyll-*a* from CI_{cyano} data was reported in Tomlinson et al. (2016) and developed using data specifically from Florida lakes
- Landsat 8; Lake Villarrica (Rodríguez-López *et al.*, 2023): multispectral Landsat 8 Collection 2 Level 1 Operational Land Imager images (L8/OLI) were used (see **Table 2**). a total of nine spectral indices that have previously been used to detect the presence of aquatic vegetation through remote sensing were included in this study. The statistical indicators of the model generated revealed that the SABI and FAI indices were the most precise in estimating Chl-a levels in Lake Villarrica.
- Sentinel 3; Large lakes and reservoirs, India (Maniyar, Kumar and Mishra, 2022): multiple indices
    - o NDCI=normalized difference chlorophyll index; Chl-a=Chlorophyll-a; SS (681) = Spectral Shape at 681 nm; SS (665) = Spectral Shape at 665 nm; CI = Cyanobacteria Index;

CI_{cyano} = Cyanobacteria Index specific to cyanobacteria only; CCD = cyanobacteria cell density

- MERIS; Lake Geneva (Soulignac *et al.*, 2018): satellite MERIS observations and the processing was done with the FUB WeW neural network algorithm (Schroeder et al., 2007). The algorithm gives a resolution of 260 × 290 m and can handle Chl-a concentrations between 0.05 and 50 µg/l.
- MERIS; Greifensee Lake, Switzerland (Odermatt *et al.*, 2012):
    - o ESA's Earth Observation Link (EOLi) listed 42 MERIS full resolution images (300 m pixels)
    - o Multiple neural network chl-a algorithms
    - o The agreement of MERIS estimates and *in-situ* measurements remains thus relatively low for all assessed weightings. This corresponds to effects of vertical heterogeneity and phytoplankton absorption efficiency
    - o MERIS and the evaluated neural network algorithms are capable to provide qualitative indicators of phytoplankton growth dynamics and water quality in small, eutrophic lakes like Greifensee (8.45 km^2)
- NASA MODISaqua; 3 large eutrophic lakes, China (Zhang *et al.*, 2021): floating algae index (FAI)
    - o we used the ratio of algal bloom area to the total water area. If the ratio was greater than 20%, the lake was defined as undergoing severe algal blooms.

surface/near surface planktonic blooms with smaller water bodies

- Sentinel 2; Irongate and Copco Reservoirs, Klamath River, USA (Kislik *et al.*, 2022):
    - o Sentinel-2 spectral indices used for chlorophyll-a identification: Normalized Difference Vegetation Index (NDVI), the Normalized Difference Chlorophyll Index (NDCI), Band 8A Band 4 (B8AB4), and Band 3 Band 2 (B3B2). The two best-performing indices across all sites were NDCI and NDVI.
- Sentinel 2; Inland waters, Latin America (Lobo *et al.*, 2021):
    - o calibrate and validate predictive algorithms for Chlorophyll-a (NDCI) and Trophic State Index classes using both in situ data and Sentinel-2/MSI data available in Google Earth Engine
    - o NDCI is used to estimate both Chl-a concentration, based on a non-linear fitting model, and TSI, based on a tree-decision model. The TSI tree decision classifies every pixel into five levels of Trophic State Index (Oligo, Meso, Eutrophic, Super, and Hypereutrophic) [**23**]
    - o To detect the algae bloom (AB), the criterion was to consider either Super-eutrophic or Hyper-eutrophic levels (i.e., Chl-a > 30.55 µg/L) as algae bloom condition. The output is binary classification, where $NDCI_{sat}$ is categorized either as non-bloom (Oligo, Meso and Eutrophic levels) or AB condition (Super and Hypereutrophic levels).
    - o the proposed algorithm presented higher uncertainty for low Chl-a values (<5 µg/L). As Chl-a increases, the algorithm accurately estimates Chl-a for concentration between 10 and 70 µg/L; the prediction's errors increase significantly above 70 µg/L [Chl-a], according to the model's residual values
- LandSat vs ground-based hyperspectral reflectance; Oklahoma lakes (Cook *et al.*, 2023):
    - o To test how published models effectively predicted cyanoHABs in Oklahoma lakes, we applied a set of chlorophyll-*a* algorithms adapted to Landsat 7 from the Landsat 8 models (Landsat 8 bands 2–6 match Landsat 7 bands 1–5) in Beck et al. (2016) (Table 1). The algorithms from the literature include the Normalized Difference Chlorophyll Index

(NDCI) (Mishra and Mishra, 2012), the Surface Algal Bloom Index (SABI) (Alawadi, 2010), the Fluorescence Line Height algorithm focusing on the blue band (FLH blue) (Zhao et al., 2010), the two-band algorithm (2BDA) (Gitelson et al., 2003), the three-band algorithm (3BDA) (Dall'Olmo and Gitelson, 2005) and the three band-like algorithm (KIVU) (Brivio et al., 2001; Kneubühler et al., 2007). We also used one established phycocyanin Landsat algorithm from the literature (Vincent et al., 2004) to compare with our Landsat phycocyanin model (Table 1).

  - All models, including our own, showed systematic bias where samples with medium to high (30–150 µg/L) observed chlorophyll-*a* values had much lower predicted values, never exceeding 30 µg/L
  - This phycocyanin model underpredicted at higher values, meaning it predicted much lower phycocyanin values than were observed (Fig. 4B). The Vincent et al. (2004) model performed better on the Oklahoma dataset than the model from this paper (Table 3.9).
  - The chlorophyll-*a* random forest model constructed using satellite data performed poorly, only explaining 3.07% of the variance
  - The best chlorophyll-*a* and phycocyanin models with ground-based hyperspectral reflectance included six band ratios (1:3, 1:5, 2:3, 3:4, 3:5, 4:5) and seven band ratios (1:2, 1:5, 2:3, 2:4, 3:4, 3:5, 4:5), respectively
  - the satellite sensors only measure chlorophyll-*a* at the surface, but *in-situ* measurements of chlorophyll-*a* are generally taken across the photic zone for mid-column bloom formers. This would cause mid-column blooming cyanobacteria or well mixed blooms to appear less concentrated or less pigmented than surface blooms (Coffer et al., 2021a). In Oklahoma lakes, for example, we frequently experience *Raphidiopsis* blooms and other non-surface bloomers (Antunes et al., 2015)

- Sentinel 2 Xin'anjiang Reservoir, China (Li *et al.*, 2022):
  - Compared with traditional methods of ship-based sampling and the use of satellite-derived C_{surf}, the proposed CIC retrieval model provides a more accurate assessment of changes in algal biomass for deep-water reservoirs
  - Our datasets cover only the formation and stationary stages of the thermal stratification period.
- DESIS hyperspectral (Legleiter *et al.*, 2022): Hyperspectral data used to identify chl-a, CI, and predicted cyanobacterial genera
  - DESIS from ISS
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-

Cyanobacterial Index (CI) and derived Cyanobacterial Cell Density (CCD)

surface/near surface planktonic blooms on larger water bodies

- MERIS, Sentinel 3 OLCI, large US lakes (Schaeffer *et al.*, 2022): CI_{cyano}
  - spectral bands centered at 665 nm, 681 nm, and 709 nm are used to assess cyanobacterial bloom biomass
  - and those centered at 620 nm, 665 nm, and 681 nm are used as exclusion criteria to prevent the quantification of non-cyanobacterial blooms.
  - Throughout this study, a pixel is classified as a cyanobacterial detection if the CI_{cyano} algorithm returns any detectable value ($CI_{cyano} > 0.0001$), indicating cyanobacteria in concentrations greater than the detection limit of the sensor.
- Baltic Sea (Konik *et al.*, 2023):
- Sentinel 3 OLCI; Lake Okochobee and St Lucie Estuary, FL USA (Reynolds *et al.*, 2023): European Space Agency's Sentinel-3 OLCI imagery processed with the Cyanobacteria Index (CI_{cyano})
- MERIS; FL and OH, USA (Mishra *et al.*, 2019):
  - MERIS Level-2 (L2) datasets were processed using the satellite automated processing system (SAPS) administered by the National Oceanic and Atmospheric Administration (NOAA).
  - The Cyanobacteria Index (CI) measures a proxy of Chl-*a* absorption and provides the cyanobacterial biomass[11,18,19,29,41].
  - For purposes of setting risk thresholds, we applied a relationship between CI and cyanobacterial cell concentration of 10^8 cells mL^{-1} per 1 unit of CI-*cyano*[11]. While the relationship[11] was developed for *Microcystis* (so we term the value as "*Microcystis*-equivalent cells"), it was validated by[15,41] for unspecified total cell concentrations of cyanobacteria in eight U.S. eastern states across New England (Connecticut, Massachusetts, Maine, New Hampshire, Rhode Island, and Vermont), Ohio, and Florida. Mean absolute percent error (MAPE) of 28.6% was reported between field-measured cyanobacteria biomass data (cells mL^{-1}) and satellite-derived cell biomass[15]. This CI algorithm has also been confirmed for detecting cyanobacterial blooms and estimating biomass (cells mL^{-1}) in other areas[18,19].
- MERIS; Clear Lake, CA, USA (Sharp *et al.*, 2021):

- The Cyanobacteria Index (CI) remote sensing algorithm was used to estimate cyanobacterial abundance in the top portion of the water column from data acquired from the Ocean and Land Color Instrument (OLCI) sensor on the Sentinel-3a satellite.
- The CI algorithm uses the multispectral MERIS sensor mounted on the Envisat satellite and the Ocean and Land Color Instrument (OLCI) sensor on Sentinel-3 because they have the correct spectral resolution to differentiate cyanobacteria from other phytoplankton. While satellite remote sensing allows for repeated sub-weekly observation of the conditions at the same location, the spatial resolution is usually coarse, ranging from 30 to 1,000 m (Kutser, 2009; Hunter et al., 2017), with most cyanobacteria-specific algorithms utilizing the MERIS and OLCI sensors, which have a resolution of 300 m.
- Using the approach in Tomlinson et al. (2016), a locally tuned equation comparing chlorophyll-*a* and phycocyanin to CI was determined for our study site. Previous proposed equations relating CI to chlorophyll-*a* are shown below (Eq. 3 from Tomlinson et al., 2016 and Eq. 4 from Stumpf et al., 2015). A least-squares linear regression approach was used to model the relationship between CI and both chlorophyll-*a* and phycocyanin specific to Clear Lake.
- The high spatial variability is also observed within each satellite pixel.

- OLCI; Large USA lakes (Coffer *et al.*, 2021b):
  - Given the spatial resolution of OLCI, a total of 2,196 lakes and reservoirs across 46 US states can be resolved (Urquhart and Schaeffer, 2020). The relatively coarse spatial resolution of OLCI results in the loss of smaller lakes as well as more narrow portions of resolvable lakes. Also excluding pixels along the land-water interface removes areas where blooms can accumulate in shoreline areas with potential recreational exposure.
  - retrievals from a passive satellite sensor can only consider contributions from aquatic constituents present to a depth of about 2 m in clear waters in the red region of the electromagnetic spectrum used for characterizing cyanobacteria (Mishra et al., 2005) and much less than 2 m in more turbid waters (Wynne et al., 2010).
- Sentinel 3 OLCI Drinking water reservoirs, USA (Coffer *et al.*, 2021a):
  - Standard Sentinel-3A OLCI Level-1B data (calibrated top-of-atmosphere radiances) were first obtained from ESA through the Copernicus program and were then processed to Level-2 imagery (surface reflectances) by the National Aeronautics and Space Administration (NASA) Ocean Biology Processing Group (OBPG; https://oceandata.sci.gsfc.nasa.gov).
  - The CI-cyano algorithm leverages spectral bands centered at 665 nm, 681 nm, and 709 nm to assess bloom biomass (Wynne et al., 2008), and those centered at 620 nm, 665 nm, and 681 nm as exclusion criteria. A bloom defined as any cyanobacterial abundance that exceeds the detection limit of the sensor, which is preliminarily estimated to be between 10,000 and 20,000 cells/mL
  - A total of 285 lakes across 44 states in the continental United States contain drinking water intakes and are observable given the spatial resolution of OLCI (300 m). Qualitative observations of bloom in the month before the satellite pass are considered.
- MERIS and OLCI; USA lakes (Whitman *et al.*, 2022): state recreational advisories as bloom indicators vs CI-cyano derived from MERIS and OLCI were obtained from the National

Aeronautics and Space Administration (NASA) Ocean Color website (https://oceancolor.gsfc.nasa.gov/projects/cyan/).

  - complete sequence of CI_{cyano} development is described in greater detail in Coffer et al., (2020)
  - bloom = CI-cyano above the algorithm detection limit of 0.0001 and the spatial extent, computed as the area of unique pixels where cyanobacteria have been detected with CI_{cyano} within the seven-day composite, was greater than or equal to 10% of the lake area.
  - out of 1,125 state reported events, 674 (60%) samples were classified as presence-presence and 451 (40%) were classified as misfit absence

- Sentinel 3; Large lakes and reservoirs, India (Maniyar, Kumar and Mishra, 2022):
  - multiple chl-a and cyanobacterial indices (CI = Cyanobacteria Index; CI_{cyano} = Cyanobacteria Index specific to cyanobacteria only; CCD = cyanobacteria cell density).
  - we validated Lunetta et al. (2015) model in Chilika Lagoon, India, with total 29 samples (*n* = 29), which were found to match-up on the same-day cloud-free satellite overpass. A significant correlation ($R^2 = 0.39$; $p < 0.01$; $n = 29$) was observed between in-situ versus satellite derived CCD and%NRMSE was estimated 21.46%. Site-specific tuning of the CCD model would be required in the future to improve the accuracy when more in-situ data become available from Indian waterbodies.

surface/near surface planktonic blooms with smaller water bodies and coastal areas

- sentinel 2, Spain (Viso-Vázquez *et al.*, 2021)
  - The spectral indices used were the Normalized Difference Water Index (NDWI), the Normalized Differences Vegetation Index (NDVI), the green Normalized Difference Vegetation Index (gNDVI), the Normalized Soil Moisture Index (NSMI), and Toming's Index
- DESIS : (Legleiter *et al.*, 2022): Cyanobacterial Index (CI)
  - Use hyperspectral data and CI to estimable cyanobacterial abundance at several water bodies

Table 2

Spectral indices used to identify waterbodies and quantify the amount of chlorophyll-a and cyanobacteria present therein. $R_{rs}(\lambda)$ denotes the remote sensing reflectance for the DESIS band centered at wavelength λ in units of nm.

Index	Equation	Source
Normalized difference water index (NDWI)	$\frac{R_{rs}(560.6) - R_{rs}(865.4)}{R_{rs}(560.6) + R_{rs}(865.4)}$	(McFeeters, 1996)
Normalized difference chlorophyll index (NDCI)	$\frac{R_{rs}(706.7) - R_{rs}(665.3)}{R_{rs}(706.7) + R_{rs}(665.3)}$	(Mishra and Mishra, 2012)
Cyanobacterial index (CI)	$-R_{rs}(680.9) - R_{rs}(662.8) - [R_{rs}(709.4) - R_{rs}(662.8)]\frac{680.9 - 662.8}{709.4 - 662.8}$	(Wynne et al., 2008)

  -

- MODIS, Florida estuary, USA (Cannizzaro *et al.*, 2019): detection of marine picocyanobacteria (*Synechococcus*) with chl-a and CI

- o Wavebands for deriving the MODIS Cyanobacteria Index, CI_{MODIS}, are the same as those used for determining MODIS Fluorescence Line Height (FLH) (667, 678, and 748 nm); and CI_{MODIS} is essentially the negative of MODIS FLH. MODIS FLH is commonly used as an indicator of coastal and estuarine eukaryotic algal blooms ([Gower et al., 2004]; [Hu et al., 2005]).
- o For CI_{MODIS}, $\lambda^- = 667$ nm, $\lambda = 678$ nm, and $\lambda^+ = 748$ nm; and $CI_{MODIS} = -SS(678)$ (Wynne, Stumpf and Briggs, 2013).
- o CI_{MODIS} threshold whereby cyanobacteria blooms were positively classified when $CI_{MODIS} > 0.0003$
- o Add $SS(488) < -0.0055$ and use dual criteria characterization - modifying the original CI approach to include SS(488) allowed weaker cyanobacteria blooms with Chl-*a* < 10 mg m^{-3} to be differentiated from seagrass-rich, non-bloom waters with high bottom reflectance

Turbidity

surface/near surface planktonic blooms on larger water bodies

- [Copernicus Global Land Service (3-products)] – large lakes

Water surface temperature

- Commonly recognized cyanobacteria are more dominant at warmer water temperatures (>25 °C) where they out-compete other organisms
- some cyanobacteria occur in cooler waters (<15 °C) (Reinl *et al.*, 2023), including under winter ice and in polar regions (Chrismas, Anesio and Sánchez-Baracaldo, 2015; Zakhia *et al.*, 2008); across trophic states
- small increases in temperature can result in significant gains in growth even if the absolute temperature is still low

surface/near surface planktonic blooms on larger water bodies

- [Copernicus Global Land Service (3-products)] – large lakes
- Clear Lake, CA, USA (Sharp *et al.*, 2021): cyanobacteria were more dominant in the lower arms of the lake that had warmer temperatures and calmer, stratified conditions
- Lake Villarrica (Rodríguez-López *et al.*, 2023): blooms in Lake Villarrica (primarily *Dolichospermum*) have manifested themselves when the temperature is higher than 18 °C
- Lake Taihu, China (Jia, Zhang and Dong, 2019): mean floating algae index associated with higher minimum temperature (better over-wintering and earlier bloom initation)
- Meta-analysis of multiple lakes, North and South America (Bonilla *et al.*, 2023a):
  - o water temperature, conductivity, pH, total nitrogen (TN), and total phosphorus (TP). To evaluate cyanobacterial trends, we used biomass (measured as total cyanobacterial biovolume; CYA_{BM}) as the response variable
  - o Temperature was not significantly related to CYA_{BM}, either alone or in interaction with any other variable. Cyanobacteria reached high biomass in our dataset across a wide range of temperatures, with the exception of the extreme ranges of the gradient (i.e., < 10 and > 30 °C) where the lowest values were observed
- Tropical/Brazil and Temperate/Canada lakes (Giani *et al.*, 2020):

- Canadian lakes: most important variables to distinguish samples of low vs higher cyanobacteria biomass were TP concentration (node 1; threshold of 86 µg/L), followed by temperature (node 2; threshold of 18.5 °C). This tree clearly shows that cyanobacteria biomass was lowest when nutrients were below 86 µg/L and water temperatures fell below 18.5 °C.
    - In Brazil (Fig. 5C), temperature was not an important variable
    - combined effect of temperature and nutrients observed in the present study, (i.e., pronounced increase in cyanobacteria when temperatures exceeded 20°C and when TP was above 100 µg/L)
- *Raphidiopsis raciborskii,* laboratory culture (Zheng *et al.*, 2023):
    - Culture at 10 °C (T_{10}), 15 °C (T_{15}), 20 °C (T_{20}), 25 °C (T_{25}), and 32 °C [range of water temperatures in tropical lakes where *Raphidiopsis* is dominant]
    - cell viability and specific growth rate of R. raciborskii showed a significant positive correlation with temperature with highest growth rate at the highest temp tested (32 °C)
    - positive growth was also determined at 20 °C and 15 °C, supporting previous laboratory and field observations
    - *R. raciborskii* has broad temperature adaptability and can sustain growth at temperatures above approximately 10 °C, with optimal growth temperatures and photosynthetic efficiency at approximately 25 °C

surface/near surface planktonic blooms with smaller water bodies and coastal areas

- Filamentous cyanobacteria, Baltic Sea (Olofsson *et al.*, 2020)
    - Temporal trends in Aphanizomenon and Dolichospermum across the Baltic Sea; relationships with changes in temperature and salinity vary across regions
        - Nodularia biovolume did not change with summertime decreasing salinity and increasing temperature across the subbasins
        - Aphanizomenon and Dolichospermum increased with decreased salinity and increased temperature in northern region, but Aphanizomenon in southern region decreased with similar decreased salinity and increased temperatures

Benthic cyanobacteria in flowing systems

- Ain River (Robichon, Robin and Dolédec, 2023):
    - Water temperature positively influenced benthic cyanobacteria development in late July (20.9 ± 0.1 °C). BC development is associated with temperatures warmer than the seasonal average (>14 °C in New Zealand rivers, Heath et al., 2015; >16 °C in the Tarn River, France, Echenique-Subiabre et al., 2018).

Stratification

surface/near surface planktonic blooms on larger water bodies

- Clear Lake, CA, USA (Sharp *et al.*, 2021): cyanobacteria were more dominant in the lower arms of the lake that had warmer temperatures and calmer, stratified conditions
- ESA Arc Lake; Great Lakes, USA (Fichot *et al.*, 2019):
    - detect lake turnover with temporal analysis of surface water temperature based on the ARC-Lake v3.0 reconstructed LSWT products

- The evolution of spring and fall overturning in each lake was determined by monitoring the migration of the 4 °C surface isotherm (4 °C thermal front) on the daily maps of LSWT generated from the ARC-Lake reconstructed data.
- Delft3d hydrodynamic model; lakes (Soulignac *et al.*, 2018):
  - comparison between measurements and simulations showed that the model is capable of reproducing the evolution of the lake thermal vertical structure on a smaller time-scale
  - our results are coherent with the PEG model which states that thermal stratification triggers the algal development in spring in deep lakes due to enhanced light availability for phytoplankton growth resulting from restrictions on the mixing depth
  - wind driven upwelling events and create surface Chl-a heterogeneities bringing potentially toxic species such as Planktothrix to the surface

Nutrients/Trophic State

surface/near surface planktonic blooms on larger water bodies

- Copernicus Global Land Service (3-products) – large lakes
- Lake Taihu, China (Jia, Zhang and Dong, 2019): nutrient loadings were only positively correlated with cyanobacteria bloom characteristics from an annual perspective
- Meta-analysis of multiple lakes, North and South America (Bonilla *et al.*, 2023a):
  - water temperature, conductivity, pH, total nitrogen (TN), and total phosphorus (TP). To evaluate cyanobacterial trends, we used biomass (measured as total cyanobacterial biovolume; CYA_{BM}) as the response variable
  - TP was the variable most strongly related to CYA_{BM}. Lower CYA_{BM} was associated with TP < 73.4 $\mu g L^{-1}$.
  - pH was significant (> 8.12), but only under conditions of high TP (> 73.4 $\mu g L^{-1}$). pH fuels cyanobacterial abundance under high nutrient conditions through a biologically mediated positive feedback
  - At a given TP concentration, waterbody depth influences whether nitrogen (also) limits cyanobacterial biomass.
- Tropical/Brazil and Temperate/Canada lakes (Giani *et al.*, 2020):
  - Canadian lakes: most important variables to distinguish samples of low vs higher cyanobacteria biomass were TP concentration (node 1; threshold of 86 µg/L), followed by temperature (node 2; threshold of 18.5 °C). This tree clearly shows that cyanobacteria biomass was lowest when nutrients were below 86 µg/L and water temperatures fell below 18.5 °C.
  - In Brazil (Fig. 5C), TP was also the most important variable (node 1; threshold 79 µg/L), followed by WRT (node 2; threshold 14 days per year), and precipitation (node 4; threshold 69 mm per month). In the tropical reservoirs, cyanobacteria biomass was lowest when TP was below 79 µg/L and water residence time was less than 14 days. In contrast, cyanobacteria biomass tended to increase when the waters were very nutrient rich, or when water residence time was greater than 14 days and regional precipitation increased above 69 mm per month (rainy season).

- combined effect of temperature and nutrients observed in the present study, (i.e., pronounced increase in cyanobacteria when temperatures exceeded 20°C and when TP was above 100 µg/L)

surface/near surface planktonic blooms with smaller water bodies

- Sentinel 2; Inland waters, Latin America (Lobo *et al.*, 2021):
    - calibrate and validate predictive algorithms for Chlorophyll-a (NDCI) and Trophic State Index classes using both in situ data and Sentinel-2/MSI data available in Google Earth Engine
    - The TSI tree decision classifies every pixel into five levels of Trophic State Index (Oligo, Meso, Eutrophic, Super, and Hypereutrophic) [**23**]

Bathymetry/Hydrodynamics

surface/near surface planktonic blooms on larger water bodies

- Clear Lake, CA, USA (Sharp *et al.*, 2021): cyanobacteria were more dominant in the lower arms of the lake that had warmer temperatures and calmer, stratified conditions
- Lake Taihu, China (Jia, Zhang and Dong, 2019): intensive precipitation (and associated increase in nutrient availability) associated with monthly and annual cyanobacterial bloom
- Sentinel 3; Large lakes and reservoirs, India (Maniyar, Kumar and Mishra, 2022):
    - Waterflow at reservoir sites is primarily controlled by dams. CyanoKhoj generated spatio-temporal maps for these sites showed a noticeable temporal change in Chl-a and CCD levels.
    - Indian monsoon typically begins in June and lasts till September, while October to December is the post-monsoon period in which the monsoon retreats.
    - Ukai Lake, Barghi Reservoir and Gandhisagar Dam, which are inland waters, become most susceptible to intense CyanoHABs during the post-monsoon season, and the blooms finally subside by late winter (Fig. 9). Hirakud Reservoir, another inland waterbody, also showed a similar trend, but the blooms persisted for a longer time and finally dissipated during the early summer months. Linganamakki, a marshy inland water site, was found to be suffering from heavy CyanoHABs for longer period throughout the year, roughly spanning from early monsoon to late summer with CCD peaks during winter. Pulicat Lake, which is not entirely inland due to the presence of coastal transitions, undergoes CyanoHABs consistently throughout the year, with long peaks in late summer/ early monsoon and almost no months bloom-free.
- NASA MODISaqua; 3 large eutrophic lakes, China (Zhang et al., 2021): floating algae index (FAI); Monthly wind speed and [surface/floating] algal bloom area showed the expected negative relationship
- Multiple lakes, North and South America (Bonilla *et al.*, 2023a):
    - water temperature, conductivity, pH, total nitrogen (TN), and total phosphorus (TP). To evaluate cyanobacterial trends, we used biomass (measured as total cyanobacterial biovolume; CYA_{BM}) as the response variable
    - shallow lakes had the highest CYA_{BM}, on average, followed by intermediate and then deep lakes, and the maximum CYA_{BM} (861 $mm^3 L^{-1}$) was found in a shallow lake located in the warm temperate region
- Tropical/Brazil and Temperate/Canada lakes (Giani *et al.*, 2020):

- In Canada, water residence time and precip were not important variables
- In Brazil (Fig. 5C), TP was also the most important variable (node 1; threshold 79 µg/L), followed by Water Residence Time (node 2; threshold 14 days per year), and precipitation (node 4; threshold 69 mm per month). In the tropical reservoirs, cyanobacteria biomass was lowest when TP was below 79 µg/L and water residence time was less than 14 days. In contrast, cyanobacteria biomass tended to increase when the waters were very nutrient rich, or when water residence time was greater than 14 days and regional precipitation increased above 69 mm per month (rainy season).
- For all lakes combined, WRT was the best explanatory variable to separate high and low cyanobacteria biomass

Benthic cyanobacteria in flowing systems

- Tropical Andes mountain stream (Rosero-López *et al.*, 2022): field experiment with before-after-control-impact study of flow;
    - flow changes also resulted in change in water temperature and nitrates
    - a significant positive effect of flow on benthic cyanobacteria biomass related with the effect on temperature and nitrate concentration increase
    - The combination of experimental manipulation, field monitoring, and a global literature survey suggests that a flow reduction beyond a threshold of about 40-60% of natural flow conditions induces abrupt shifts in cyanobacteria biomass.
- Yangtze River, China (Shang *et al.*, 2023): reduced flow (flow discharge < 12,900 m^3/s) shifted towards benthic cyanobacteria dominance
- Buffalo River, USA (Legleiter and Hodges, 2022):
    - Eight-band images with 2 m and 1.81 m pixels were acquired by the WorldView3 satellite. Cloud-free, four-band, 0.5 m pixel images from SkySat.
    - Used the optimal band ratio analysis (OBRA) algorithm introduced by Legleiter et al. [**42**] and refined by Legleiter and Harrison [**43**], to produce bathymetric maps of the Gilbert and Maumee reaches from each of the remotely sensed datasets described above.
    - Overall, these results confirmed that reliable estimates of river bathymetry could be derived from readily available image data to provide an additional source of information for mapping benthic algae in shallow, clear-flowing streams with depths up to approximately 2 m.
- Ain River (Robichon, Robin and Dolédec, 2023):
    - *Phormidium* sp. was the major component of cyanobacteria biovolume (Fig. 6A). Its biovolume reached a maximum in mid-July and late July during the low flow period and was significantly at its lowest in June and August during periods of high flow variability.
    - Hydraulic variables were the main source of variation in each campaign (variance explained ranged from 14.5 % to 19.4 %).
    - in New Zealand benthic cyanobacteria decreased at 2-3× median/mean flows (Heath et al., 2011; Wood et al., 2017). Translated to the Ain River that has a yearly average discharge of 103 $m^3.s^{-1}$, this would mean that flushing flows with discharges from 206 to 309 $m^3.s^{-1}$ would be necessary to reduce BC development.

Climate events

- Sentinel 2; Rio de la Plata estuary, Uruguay (Aubriot *et al.*, 2020): ENSO events increase freshwater discharge into the Río de la Plata, producing significant changes in terms of turbidity front, nutrient dynamics and phytoplankton composition (Brugnoli et al., 2018; Nagy et al., 2008, 2014; Sathicq et al., 2015); ultimately with cyanoHABs on the coast (Risso et al., 2018).

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