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Using Remote Sensing to Monitor Water Quality in Climate and Wildfire Stressed California Reservoirs

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Using Remote Sensing to Monitor Water Quality in Climate and Wildfire Stressed California Reservoirs

Dissertation submitted in partial satisfaction of the requirements
for the degree Doctor of Philosophy

in

Environmental Systems

by

Brittany Lopez Barreto

Committee in charge:
Erin L. Hestir, Chair
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The Dissertation of Brittany Lopez Barreto is approved, and it is acceptable in quality and form for publication on microfilm and electronically:

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University of California, Merced

2024

Dedication

I would like to dedicate this work to my mother, Emidgia Clorinda Barreto, and my husband, Nicholas Esai Martinez. This has, and always will be, for us and our family.

Without my mother's support, encouragement, love, and resilience she has shown me time and time again, I would be aimless. Gracias.

Without my husband's patience, friendship, and love, I would be lost. Thank you.

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Acknowledgements

I've known I wanted to be a scientist ever since I won the highest science award in middle school. That same year, I also was nominated "most likely to succeed" and received the highest award dedicated towards college prep. I've known that I was going to go to college, and probably a Master's degree. This was the minimum of what I expected of myself given the immense support system I've had. Still, looking back I cannot believe what I have accomplished during my time as a graduate student. Younger (but not much shorter) me would not believe it, mainly because I think I would not be willing to even try. At some point, I stopped aiming so high because of my fear of failure. I would rather tell myself, "No" than have someone else. Somehow, and thankfully, I landed one of the most prestigious STEM grants for graduate students, successfully led an upper-division course at a UC, fully covered to travel abroad to share my work and findings and the fortune of having job offers in this intense job market. I have thus learned and ingrained in myself that the answer is always "No" if one does not ask.

I am thankful to my advisor, Erin Hestir, for pushing and testing me as much as you have. You have been the greatest mentor a woman like me could have, and I am fortunate to have such a strong woman in my corner this whole time. I would also like to thank my committee member's Marc Beutel, Natasha Stravos, Christine Lee and Crystal Kolden for your immense and invaluable feedback, patience, knowledge, and overall support.

Of course, none of this work and the ability to share it would be possible without the funding from my NASA FINESST Grant (80NSSC21K1622), the Center for Information Technology Research and the Banatao Institute, and UC Merced internal fellowships.

Special thanks to my family: my mom, Clory, my forever motivation. My husband, Nick, who is my sunshine protector. My dad for always loving me unconditionally. My cousins, Valerie, Deniese, and Guny for being the big sisters I've always wanted. My dearest and closest friends: Jessie, Elizabeth, Arianna, Ashley, Sergio, Steve, Johanna, Rubio, Max, Josh, Victor, John, and Justin. Thank you for the laughs, distractions, and friendship, where most have been 15+ years. What a trip. I want to thank my colleagues, friends, and peers that I have made at UCM such as Dr. Christiana A,. Fatima, Gabriela, Melisa, Dr. Gustavo F.D., Humberto IV, Yelenka, Ana Grace, Dr. Dulcinea A., Jacob, Tasos, and Dr. Maia P. Thank you for your help, guidance, and making my time at Merced a fun one.

The journey here has not been easy, and it has been a long one. I have had a lot of great personal milestones, such as replacing my mom's car, helping buy our family home and getting married. I will look back at this period of my life as a stressful time, but a time that laid the foundation for me and my family's future.

Curriculum Vitae

Email: Brittany Lopez Barreto

EDUCATION

University of California, Merced Expected Graduation: July 2024
Doctor of Philosophy in Environmental Systems
Using Remote Sensing to Monitor Water Quality in Climate and Wildfire Stressed California Reservoirs

University of California, Davis Graduation: June 2018
Bachelor of Science in Environmental Science and Management with a Watershed track

RESEARCH EXPERIENCE

Future Investigator in NASA Earth Science and Technology (FINESST)
2021 – Present *Future Investigator (FI)*
This three-year proposal uses remote sensing to monitor reservoir and lake water quality in California, with a special interest in the impacts of wildfire. We use satellite data from Sentinel-2 & 3 to create a multi-decadal time series to measure variables such as turbidity, chlorophyll-a and cyanobacteria. This study incorporates multiple environmental and climatic variables (i.e land cover class, impervious surface, precipitation, wind speed, etc.), as well as the local fire regime (frequency, intensity, distance to nearest drainage) to determine their degree of influence on water quality.

University of California Merced *Graduate Research Assistant*
2018 – 2019 Advisor: Dr. Erin Hestir; Project PI: Dr. Christine Lee
Research collaboration efforts with NASA's JPL for water quality mapping in the Sacramento San Joaquin Delta. Provided maps, R coding notebooks and documentation to collaborators for AVIRIS-NG hyperspectral data.

Consortium of Universities for the Advancement of Hydrologic Science (CUAHSI), National Water Center Innovators Program Summer Institute
June – July 2019 *Intern*
The initiative of the program was to create a parsimonious runoff generation modeling hydroregions. We compared TOPMODEL, which uses watershed topography to predict subsurface and overland flow, against our version of TOPMODEL, where soil and groundwater characteristics were implemented.

SKILLS

• GIS/Remote Sensing Image Analysis: ENVI, ArcGIS, QGIS, ACOLITE, and SNAP
• Programming Languages: Proficient - R. Literate – Python and Unix Shell Scripting
• Fluent in Spanish

CONFERENCE PRESENTATIONS AND TALKS

1) **Lopez Barreto, B**., Hestir, E., Lee, C., Stavros, E.N. Cyanobacterial Trends in Major California Reservoirs Using Multispectral Satellite Remote Sensing, IEEE International Geoscience and Remote Sensing Symposium (IGARSS), July. 9, 2024. In person. (Oral)
2) **Lopez Barreto, B**., Hestir, E., Lee, C., Beutel, M. Satellite Remote Sensing to Support Harmful Algal Bloom Monitoring and Recreational Health Advisories, Center for Information Technology Research and the Banatao Institute (CITRIS) Emerging Technology for Human Health and Water Systems, March 6, 2024. In person, USA, CA. (Invited Oral Presentation)
3) **Lopez Barreto, B**., E.N, Stavros, Lee, C., Hestir, E. Evaluating Wildfire Impacts on Cyanobacterial Trends for Inland Waters, Ocean Science Meeting, Feb. 19, 2024. In person, USA, LA. (Oral)
4) **Lopez Barreto, B**., Hestir, E., Lee, C., Beutel, M. Using Remote Sensing to Support Harmful Algal Bloom Monitoring and Recreational Health Advisories in a California Reservoir, International Ocean Colour Science Meeting, November 16, 2023. In person, USA, FL. (Poster)
5) **Lopez Barreto, B**., Hestir, E., Lee, C., Beutel, M. Remote Sensing of Chlorophyll-a as a Measure of Cyanotoxins in San Luis Reservoir, ASLO Aquatic Sciences Meeting 2023, June. 5, 2023, Palma de Mallorca, Spain. In person, CA. (Oral)
6) **Lopez Barreto, B**., Hestir, E., Lee, C., Beutel, M. Remote Sensing-based Chlorophyll-a as a Proxy for Harmful Algal Bloom Public Health, NASA Carbon Cycle & Ecosystems Joint Science Workshop, May 9, 2023, Maryland. In person, CA. (Oral)
7) **Lopez Barreto, B**., Fire effects on watersheds across the Western US, University of Colorado Boulder, Environmental Data Seminar, June. 14, 2022. (Invited Oral Presentation).
8) **Lopez Barreto, B**., Hestir, E. The Assessment of Post-Wildfire Effects on Cyanobacteria in California Water Supply Reservoirs Using Remote Sensing, 2021 AGU Fall Meeting, Dec. 17, 2021. AGU Fall Meeting, In person, LA. (Poster)
9) **Lopez Barreto, B.**, Using Satellite Data to Determine the Relationship between Wildfire and Cyanobacteria in California Water Supply, UC Davis's 8th Annual One Health Symposium: One Health Approach to Innovation, Nov. 6, 2021. Virtual. (**Oral Presentation**)
10) **Lopez Barreto, B.**, The Assessment of Post-Wildfire Effects on Cyanobacteria in California Water Supply Reservoirs Using Remote Sensing, NASA Ocean Color Research Team, Early Career Lightening Talks, Oct. 27, 2021, Virtual. (**Oral Presentation**)
11) **Lopez Barreto, B.**, Hestir, E. Multi-decadal Post-fire Water Quality Trends in California Lakes and Reservoirs, 2020 AGU Fall Meeting, Dec. 10, 2020, AGU Fall Meeting, Virtual. (**Poster**)
12) **Lopez Barreto, B.**, Post-fire Effects on Cyanobacteria in Lakes and Reservoirs Using Remote Sensing, Oct. 15, 2020, California Lake Management Society, Virtual. (**Oral Presentation**)
13) **Lopez Barreto, B.**, Antolini, F., Baron, S., Jahan Dolan, I. A Study on Parsimonious Models in Catchments Generating Saturation Excess Runoff, 2019 AGU Fall Meeting, Dec. 13, 2019, AGU Fall Meeting, San Francisco, CA, In person. (**Poster**)

PUBLICATIONS

1) **Lopez Barreto, B**., Hestir, E., Lee, C., Stavros, E.N. (2024) Cyanobacterial Trends in Major California Reservoirs Using Multispectral Satellite Remote Sensing, IEEE International Geoscience and Remote Sensing Symposium (IGARSS) (**Conference Paper**)
2) **Lopez Barreto, B.**, Hestir, E., Lee, Christine., Beutel, Marc. (2024). Satellite Remote Sensing: A Tool to Support Harmful Algal Bloom Monitoring and Recreational Health Advisories in a California Reservoir. AGU, *GeoHealth*. https://doi.org/10.1029/2023GH000941.
3) Chadwick, K. D., Davis, F., Miner, K [and 110 others including **Lopez Barreto, B**] (**In Review**).
4) Nesslage, J., **Lopez Barreto, B.,** Weingram, A., Hestir, E. (2023). A Machine Learning Approach For High Resolution Fractional Vegetation Cover Estimation Using Planet Cubesat and RGB Drone Data Fusion, 2023 IEEE International Geoscience and Remote Sensing Symposium (IGARSS, California), United States. (**Conference Paper**)
5) Ade, C., E.L. Hestir, D.M. Avouris, J. Burmistrova, C. Nickles, A.M. Lopez, **B. Lopez Barreto**, J. Vellanoweth, R. Smalldon, and C.M. Lee. 2023. SHIFT: Ramses Trios Radiometer Above Water Measurements, Santa Barbara Sea, CA. ORNL DAAC, Oak Ridge, Tennessee, USA. https://doi.org/10.3334/ORNLDAAC/22343 (**Dataset**)
6) Antolini, Federico., Baron, S., **Lopez Barreto, B.,** Jahan Dolan, I. "A Study on Parsimonious Models in Catchments Generating Saturation Excess Runoff." *National Water Center Innovators Program Summer Institute Report 2019*, vol. 16, National Water Center Innovators Program, 2019, pp. 45–56 **(Technical Report)**

TEACHING EXPERIENCE

UC Merced – ENVE 152/252: Remote Sensing of the Environment — Spring 2024
Lab Instructor (Dual undergrad/graduate) — Course Instructor*:* Dr. Erin Hestir
UC Merced – ENGR 180: Spatial Analysis & Modeling — Fall 2023
Course Instructor
UC Merced – ENGR 180: Spatial Analysis & Modeling — Spring 2021
Lab Instructor — Course Instructor*:* Dr. Angel S. Fernandez Bou
UC Merced – ENVE 152: Remote Sensing of the Environment — Fall 2020
Lab Instructor — Course Instructor*:* Dr. Erin Hestir
UC Merced – ESS 050: Ecosystems of California — Fall 2019 - Spring 2020
Teaching Assistant Course Instructor*:* Dr. John Williams
UC Davis – LDA 150: Introduction to GIS — 2017-2018
Students of Academic Success Specialized Tutor

MENTORING EXPERIENCE

- Mentor for Center for Information Technology Research in the Interest of Society (CITRIS) Expanding Diversity and Gender Equity in Tech Initiative (EDGE) in STEM Mentoring program for women in tech initiative for STEM students (2021)
- Invited speaker (2020, 2021, 2022, 2023 & 2024) for Valle de Exploracion CITRIS's women in tech initiative for STEM students from UC Merced, CSU Stanislaus, Merced.

- Panelist (2021 and 2023) for UC Merced's Expanding Your Horizons (EYH), symposium for middle school girls to engage in exciting and diverse experiences STEM careers have to offer.

HONORS, GRANTS AND AWARDS

- UC Merced Environmental Systems Professional Development Award (2024, 2023) – US $750
- NASA Carbon Cycle & Ecosystems Joint Science Meeting's Best Talk for: Research Most Impactful for People and Communities (2023)
- NASA PACE (Plankton, Aerosol, Cloud ocean Ecosystem) workshop (2022) – $750
- NASA FINESST Grant (2021) – $135k
- Expanding Diversity and Gender Equity Mentor (2021) – US $925
- UC Merced Environmental Systems Bobcat Summer Award (2020) – US $3,400
- UC Merced Environmental Systems Professional Development Award (2020, 2019) – US $1,000
- California Lake Management Society (CALMS) (2020) Summer Fellowship - $1,250
- CUAHSI Travel Grant (2019): NCAR WRF-Hydro Modeling Training – US $500
- CUAHSI Travel Grant & Stipend for National Water Center Innovators Program – US $2,800

Dissertation Abstract

Using Remote Sensing to Monitor Water Quality in Climate and Wildfire Stressed California Reservoirs

By
Brittany Lopez Barreto

Doctor of Philosophy, Environmental Systems
University of California, Merced, 2024
Dr. Erin Hestir, Graduate Advisor

The increasing frequency of cyanobacterial harmful algal blooms (cyanoHABs) in California's inland waters poses significant risks to public health and recreational water use. Wildfires, by increasing nutrient runoff and altering water temperature and light conditions, may exacerbate the occurrence of cyanoHABs. As wildfires become more frequent and severe in California, understanding their effects on water quality is essential. This dissertation leverages satellite remote sensing (SRS) to monitor cyanoHABs, quantify their temporal and spatial trends on a large scale, and explore the role of wildfire as a driver of cyanoHABs across the entire state of California. SRS provides temporally dense and spatially explicit data, which is crucial for timely cyanotoxin risk assessments and could enhance traditional in-situ sampling methods. Chapter 1 provides a framework for evaluating the public health utility of SRS for enhancing global cyanotoxin monitoring, using San Luis Reservoir as a case study. The findings indicate that public health alerts derived from SRS and World Health Organization guidelines correspond highly with public health advisories issued by state authorities based on laboratory toxin analyses. Chapter 2 expands on these findings with four additional lakes, demonstrating that point-based data outperforms lake-wide summaries. Lake-wide approaches offer a broader perspective but often underestimate the true variability and potential hotspots within a lake. This chapter also identified lakes with persistent high advisory levels of cyanoHABs across the state (74 lakes in total). Chapter 3 investigates the relationship between wildfires and cyanoHABs across California, finding a reduction in differences between burned and unburned lakes from 2016 to 2022, along with increased bloom occurrences. Although most sites didn't show a significant post-fire increase in cyanobacteria alerts, those that did often saw increases, with some recovering by the second year. The findings from this dissertation underscore the need for more extensive studies and long-term monitoring to address the impacts of changing climate and wildfires on water quality and public health.

Chapter 1: Introduction

Monitoring and researching cyanobacteria is of paramount importance due to their significant implications for public health, ecosystem integrity, and water resource management. Cyanobacteria can produce toxins (Smayda, 1997; Stumpf & Tomlinson, 2007), creating cyanobacterial harmful algal blooms (cyanoHABs), that pose serious health risks to humans and animals, including liver damage, neurotoxicity, and gastrointestinal illness (Erdner et al., 2008; Backer et al., 2013). These blooms can also disrupt aquatic ecosystems by depleting oxygen levels, causing fish kills, and altering food webs (Paerl et al., 2011). In recreational waters, cyanoHABs can lead to beach closures and economic losses for communities dependent on tourism (Hoagland et al., 2002; Stroming et al., 2020) and for individual medical costs (DeFlorio-Barker et al., 2018; Stroming et al., 2020). Therefore, understanding the dynamics of these blooms, their triggers, and their impacts is essential for protecting public health and maintaining the ecological balance of aquatic environments.

The urgency of monitoring cyanobacteria is heightened by the increasing frequency and intensity of climate change-induced phenomena, such as wildfires, droughts, and extreme weather events (Gámez et al., 2019; de Barroso et al., 2018; Lehman et al., 2017; García-Prieto et al., 2012). Wildfires, for instance, can significantly alter watershed dynamics by increasing nutrient runoff, which in turn fuels cyanoHABs (Neary et al., 2005; Sheridan et al., 2007; Emelko et al., 2011). Elevated temperatures and altered precipitation patterns associated with climate change can further exacerbate bloom conditions (Smith et al., 2009; Bladon et al., 2014), creating a feedback loop that intensifies the frequency and severity of blooms. Consequently, it is crucial to integrate climate change projections into cyanobacteria research to predict future bloom scenarios and develop adaptive management strategies.

Remote sensing technology offers a powerful tool to enhance the monitoring and management of cyanobacteria in the context of these environmental changes. Satellite remote sensing (SRS) enables the continuous, large-scale observation of water bodies, providing timely and spatially comprehensive data on bloom dynamics (Urquhart et al., 2017; Coffer et al., 2021). This technology can detect cyanobacteria changes in presence and intensity (Lunetta et al., 2015; Ruiz-Verdú et al., 2008; Wynne et al., 2008), allowing for early warning systems and more accurate risk assessments. The integration of SRS with traditional in-situ sampling can improve the precision and reliability of monitoring programs, offering a cost-effective solution for covering vast and remote areas that are otherwise difficult to access (Urquhart et al., 2017; Schaeffer et al., 2022). By leveraging remote sensing, researchers and policymakers can better understand the spatial and temporal patterns of cyanoHABs, implement more effective intervention measures, and ultimately protect public health and aquatic ecosystems from the growing threats posed by climate change and wildfires.

Chapter 1 is a case study in San Luis Reservoir, a key infrastructure in California's water infrastructure, to determine if using SRS-derived chlorophyll-a (chl-a) and/or cyanobacteria as proxies for cyanotoxins. Chl-a is a common water quality metric, unlike cyanobacteria and cyanotoxins, correlated with cyanobacteria. The World Health Organization (WHO) recently updated their cyanoHAB guidance values (GVs) to be based on chl-a concentration, enabling widespread monitoring using chl-a proxies. We used Sentinel-2 (S2) and Sentinel-3 (S3) to map chl-a and cyanobacteria, classifying chl-a values according to WHO GVs, and compared them to cyanotoxin advisories from the California Department of Water Resources (DWR) for 2016 to 2022. We found high agreement rates between DWR advisories and SRS, with S3-derived cyanobacteria slightly outperforming chl-a (83% vs 79%). SRS-based chl-a GVs can serve as early indicators for exposure advisories and triggers for in situ sampling, improving public health warnings and filling data gaps with greater spatial information than in-situ measurements alone.

Chapter 2 expands the work and findings from Chapter 3 with an additional four lakes owned by the DWR for 2016 to 2023. This work further supports the use of SRS-derived cyanobacteria to use as a proxy for cyanotoxins since there was a strong agreement (overall accuracy = 72% and balanced accuracy = 80%) across multiple lakes spanning diverse climates and ecosystems. Point-based and lake-wide cyanobacteria summaries were compared against cyanotoxins to test the effectiveness of either method. Both measures provide reasonable agreement, however point-based performed better, demonstrating a high accuracy in detecting localized blooms. Because the rates of agreement did vary site-by-site, in-situ data should be still used to help establish a better comprehension of the toxicity rates of the lakes. From these reasonable results, we did a statewide assessment of the frequency of cyanoHAB alerts for lakes resolvable from SRS. Of the 76 number of lakes, eight of them were frequently in exceedance (>25%) of WHO levels for cyanobacteria and primarily located in Southern California.

Chapter 3 investigates the effect of wildfires on cyanoHABs for the same statewide resolvable lakes used in Chapter 2. This chapter includes an earlier time period, 2008 to 2012, in our study compared to the previous chapters. From 2008 to 2011, cyanoHAB alerts were generally less frequent, with 35 lakes showing no cyanobacteria levels above the WHO99 guideline values. However, from 2016 to 2022, there was a noticeable increase in both the number and size of alerts, with only eight lakes showing no signs of cyanoHAB alerts, indicating more frequent and widespread cyanobacteria blooms across the state. Findings proved that lakes with wildfires in their watersheds had fewer cyanoHAB alerts than those that remain unburned, although statistically significant, the differences were relatively small. The majority of lakes analyzed for differences in cyanobacteria alerts before and after wildfires showed no significant change. In the first year post-fire, seven lakes showed a significant increase in cyanoHAB alerts, while three decreased. Two years post-fire, eleven lakes had significant increases in alerts, and all sites that previously decreased recovered. Nine lakes shifted between significant and non-significant change in cyanoHAB alerts between both periods. Given the large-scale nature of this study, further research is necessary to disentangle the specific contributions of wildfire activity, climate change, and land use changes to improve the understanding of cyanoHABs and wildfire. This research underscores the vital role of remote sensing in monitoring and mitigating the ecological impacts of wildfires on water quality.

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Ruiz-Verdú, A., Simis, S. G. H., de Hoyos, C., Gons, H. J., & Peña-Martínez, R. (2008). An evaluation of algorithms for the remote sensing of cyanobacterial biomass. Remote Sensing of Environment, 112(11), 3996–4008. https://doi.org/https://doi.org/10.1016/j.rse.2007.11.019

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Chapter 2: Satellite Remote Sensing: A Tool to Support Harmful Algal Bloom Monitoring and Recreational Health Advisories in a California Reservoir

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Keywords: remote sensing, harmful algal blooms, cyanobacteria, cyanotoxins, chlorophyll-a, Sentinel-2, Sentinel-3, California

*This chapter is published in AGU's GeoHealth. Lopez Barreto, B. N., Hestir, E. L., Lee, C. M., & Beutel, M. W. (2024). Satellite remote sensing: A tool to support harmful algal bloom monitoring and recreational health advisories in a California reservoir. GeoHealth, 8, e2023GH000941. https:// doi.org/10.1029/2023GH000941

Abstract:
Cyanobacterial harmful algal blooms (cyanoHABs) can harm people, animals, and affect consumptive and recreational use of inland waters. Monitoring cyanoHABs is often limited. However, chlorophyll-a (chl-a) is a common water quality metric and has been shown to have a relationship with cyanobacteria. The World Health Organization (WHO) recently updated their previous 1999 cyanoHAB guidance values (GVs) to be more practical by basing the GVs on chl-a concentration rather than cyanobacterial counts. This creates an opportunity for widespread cyanoHAB monitoring based on chl-a proxies, with satellite remote sensing (SRS) being a potentially powerful tool. We used Sentinel-2 (S2) and Sentinel-3 (S3) to map chl-a and cyanobacteria, respectively, classified chl-a values according to WHO GVs, and then compared them to cyanotoxin advisories issued by the California Department of Water Resources (DWR) at San Luis Reservoir, key infrastructure in California's water system. We found reasonably high rates of total agreement between advisories by DWR and SRS, however rates of agreement varied for S2 based on algorithm. Total agreement was 83% for S3, and 52-79% for S2. False positive and false negative rates for S3 were 12% and 23%, respectively. S2 had 12-80% false positive rate and 0-38% false negative rate, depending on algorithm. Using SRS-based chl-a GVs as an early indicator for possible exposure advisories and as a trigger for in-situ sampling may be effective to improve public health warnings. Implementing SRS for cyanoHAB monitoring could fill temporal data gaps and provide greater spatial information not available from in-situ measurements alone.

2.1 Introduction

Harmful algal blooms (HABs) are defined as an increase in phytoplankton concentration that has an adverse impact on aquatic environments and/or people. When cyanobacteria, also known as blue-green algae, produce HABs, human and wildlife health are threatened because cyanobacteria often produce toxins (Smayda, 1997; Stumpf and Tomlinson, 2007). Freshwater HABs occur worldwide and acute exposure to the cyanotoxins created by cyanobacteria HAB events (cyanoHABs) can lead to gastrointestinal illness. Chronic exposure to cyanotoxins can lead to liver damage, and recreational exposure can result in respiratory and skin irritation (Erdner et al., 2008). Wildlife are also affected by exposure to toxins released during blooms that can lead to illness or death (Backer et al., 2013). Subsequent hypoxia in the water body following HABs may contribute to fish kills and other detrimental ecosystem effects (Paerl et al., 2011). A major goal of water management and public health authorities is to monitor and eventually forecast cyanoHABs at local, regional, national, and global scales to inform and protect public health (Schaeffer et al., 2018; Stroming et al., 2020).

Because of the human health concerns posed by cyanotoxins, the World Health Organization (WHO) has issued guidance on exposure to cyanoHABs. Until recently, a commonly used method was based on cell counts. Using a microscope, an analyst can directly assess the presence of cyanobacteria by counting the number of cells (Sklenar, 2016). While it is a relatively straightforward procedure, accurate quantification is time consuming and requires careful quality control (Chorus and Bartram, 1999). Because of the laborious and costly nature of this approach, other methods have been suggested by the WHO, such as using chlorophyll-a (chl-a) as a proxy for water bodies where blooms are dominated by cyanobacteria.

In the United States, various state and regional authorities also have guidance for public health exposure and warnings for drinking water reservoirs and recreational water bodies impacted by HABs. For example, in California (CA), the Department of Water Resources (DWR) is the responsible authority for monitoring HABs at key water intake structures, and issues guidance based on the concentration of four specific cyanotoxins: microcystins, saxitoxins, cylindrospermopsin, and anatoxin-a. The toxin concentrations are measured in the laboratory using analytical biochemistry assays (typically via enzyme-linked immunosorbent assay, ELISA, (Sklenar, 2016)). The voluntary guidance relies on the science presented in the California Office of Environmental Health Hazard Assessment's (OEHHA) risk assessment for microcystin, anatoxin-a and cylindrospermopsin (OEHHA, 2012). The trigger level of 0.8 μg/L microcystin prompts increased monitoring and the placement of a caution sign that advises people, pets and livestock be kept away from the water and scum. A trigger warning of 6 μg/L microcystins prompts a warning stating that swimming is not recommended, and that pets and livestock should be kept away from the water. Both of OEHHA's action levels are based on the short-term rat ecotoxicology study by Heinze (1999). The WHO (1999) suggests a concentration of 20 μg/L microcystin as a warning level for the protection of human health based on the sub-chronic mouse study by Fawell et al. (1994; 1999a).

In recognition of the challenges associated with toxin monitoring, including access to specialized equipment, many studies have either used or promoted the use of other water quality variables that are much easier to measure (e.g., chlorophyll-a) as a proxy for potential toxin exposure (Chorus and Bartram, 1999; Hunter et al., 2009; Tebbs et al., 2013; Stumpf et al., 2016). The WHO has recently changed its guidance on public health warnings for exposure to toxins from cyanoHABs (Chorus and Welker, 2021), specifically linking chl-a to cyanotoxins in water bodies known to have cyanobacteria (Table 1). This has simplified monitoring for potential public exposure because chl-a is a readily measured water quality variable; it is easily monitored from a variety of accessible technologies, including laboratory-based spectrophotometry or fluorometry of water samples (Arvola, 1981; Johan et al., 2014; Basak et al., 2021), in-situ optical fluorometry instruments (Campbell et al., 1998; Stirbet et al., 2019), and increasingly, satellite remote sensing (SRS) (Stumpf and Tomlinson, 2007; Urquhart et al., 2017; O'Reilly and Werdell, 2019; Seegers et al., 2021; Gons et al., 2012; Moses et al., 2012).

Of the measurement technologies available to measure chl-a, SRS offers unique capabilities: it provides continuous spatial coverage over large areas with systematic, repeated visits that can be collated into a time series. This can enable better understanding of spatial and temporal patterns of surface water quality. Chl-a has been successfully measured from satellites for decades (Gitelson, 1992; Wynne et al., 2008, 2010), and has been used to support detection of HABs (Anderson, 2009; Kutser et al., 2006; Dekker et al., 2018; Papenfus et al., 2020). Of the currently operational Earth observing satellites, the European Space Agency's (ESA) Sentinel-2 (S2) provides one of the best combinations of spatial, temporal, and spectral coverage for chl-a for inland waters (Bramich et al., 2021). S2 is a constellation of two satellites, Sentinel-2A and Sentinel-2B. Each has a 10-day repeating orbit and combined create a revisit time of 5-days over an area. Each S2 satellite carries a MultiSpectral Instrument (MSI) with 13 spectral bands that measure across the visible to shortwave infrared region. The spatial resolution of this satellite varies (10, 20 and 60-meters) depending on the band. S2's "red-edge" bands (measuring within the visible red and near infrared) are well suited to chl-a detection by taking advantage of the spectral peak phytoplankton have near 700 nm. Spectral coverage in this range is beneficial for aquatic environments since colored dissolved organic matter (CDOM) and non-algal particles (NAP) can confound algorithms in shorter wavelength visible bands (Bramich et al., 2019, Gitelson et al., 1992, Gitelson et al., 2008).

Cyanobacteria contains a specific pigment, phycocyanin, which has an absorption maximum near 620-nm that allows for successful cyanobacteria estimation from some satellite sensors (Ruiz-Verdú et al., 2008; Wynne et al., 2008; Lunetta et al., 2015). Unfortunately, few current and operational satellites have the spectral resolution required to detect the phycocyanin absorption feature. Envisat's MERIS (Medium Resolution Imaging Spectrometer) was designed for aquatic targets and was used for cyanobacteria estimation from 2002-2012, when it was decommissioned. Sentinel-3's (S3) Ocean and Land Colour Instrument was launched in 2016 and has the spectral bands to detect phycocyanin and enable estimates of cyanobacteria. S3 currently underpins an operational cyanoHABs monitoring system developed through a multi-agency effort led by the Environmental Protection Agency (EPA), called the Cyanobacteria Assessment Network (CyAN). Both MERIS and Sentinel-3 have suitable spectral resolution and frequent revisit time (1-2 days) that make them attractive for cyanoHAB monitoring, but their spatial resolution is limited (300-m x 300-m pixels).

The use of chl-a and cyanobacteria pigments as reasonable proxies for toxin monitoring has been demonstrated by several studies across a range of different water bodies. Matthews et al. (2014) used chl-a products from the MERIS sensor to demonstrate the ability to identify cyanobacteria-dominated blooms in one marine setting and, later, this was extended to three eutrophic reservoirs in South Africa (Matthews and Bernard, 2015). In Tomlinson et al. (2016), they used the Cyanobacteria Index (CI) to track HABs across lakes in Florida using MERIS, and Seegers et al (2021) expanded this effort across the United States. The relationship of chl-a and cyanobacteria has also been shown using spectrophotometry (Randolph et al., 2008; Sendersky et al., 2017).

The use of proxies is not without its limitations, however. The relationship between pigments such as chl-a and toxins can vary over time based on the dynamics of bloom formation and as species composition and dominance varies (Kudela et al., 2015). For example, Stumpf et al. (2016) showed that SRS of chl-a and phycocyanin can be used to estimate cyanobacterial toxins if a model is established between measured pigments and toxins. They found that a relationship can remain constant for days to weeks in a lake, but over longer periods the relationship can weaken and may lead to large errors. Furthermore, just because cyanobacteria are present does not mean that they are necessarily toxin producing (Carmichael, 2001) and cyanotoxins do not have any optically detectable characteristics, which limits monitoring. The United States 2007 National Lakes Assessment reported that detected or high chl-a rates does not always lead to cyanoHABs; they found that only 27% of cases that indicated a recreational WHO risk through cyanobacterial abundance, microcystin or chl-a had any actual cyanotoxin risk (Loftin et al., 2016).

Given the variability in SRS of chl-a and cyanobacteria as a proxy for assessing cyanotoxin risk, there remains a need to better quantify the uncertainty of proxies relative to public health advisory levels. The objective of this study is to evaluate SRS-based chl-a and cyanobacteria proxies for cyanotoxin health advisories using a major multi-use reservoir in California's water system, San Luis Reservoir (SLR), as a case study. This study utilizes data from ongoing toxin monitoring conducted by the DWR to quantify the agreement between DWR toxin-based public health advisories and the new 2021 WHO (WHO21) chl-a based guideline values when applied to both field samples and SRS of chl-a from the S2 satellite sensors. We further evaluate the agreement between DWR advisories and the previous 1999 WHO (WHO99) cyanobacteria cell-count based guidance applied to the CyAN satellite product derived from the S3 satellite sensors.

2.2 Materials and Methods

2.2.1 Study Site

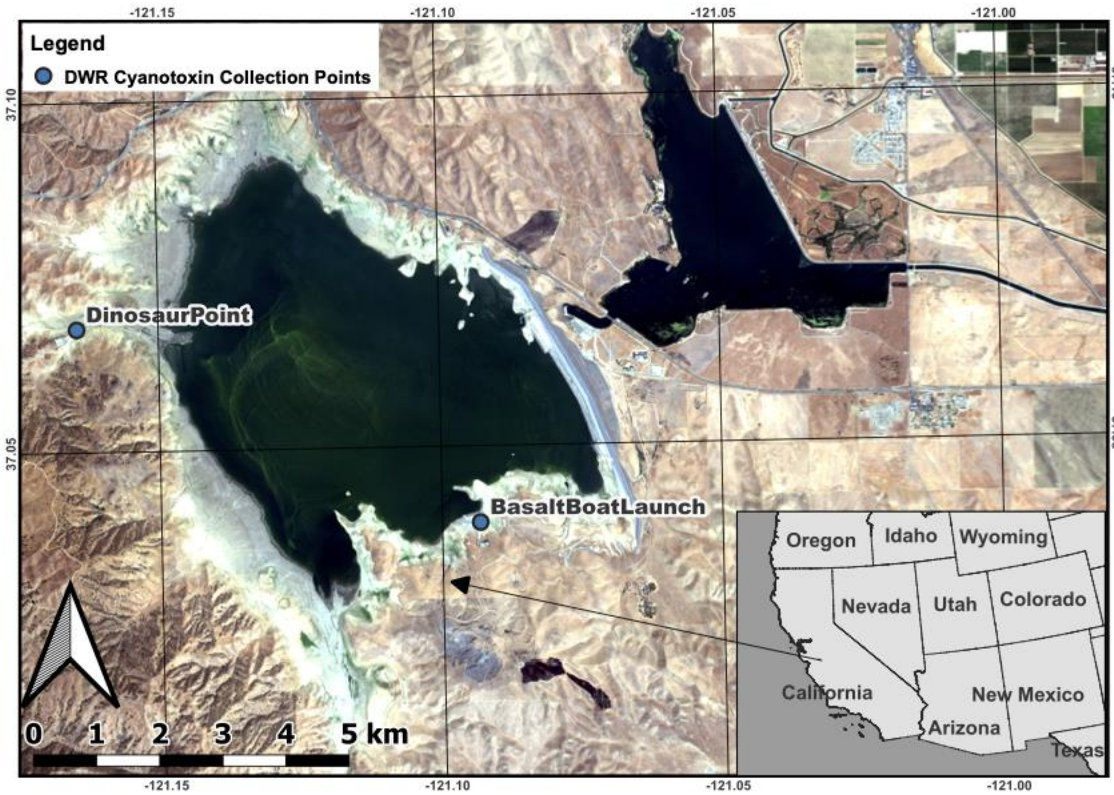

Figure 2-1. San Luis Reservoir in Los Banos, California, United States. Blue points are approximate locations where the California Department of Water Resources (DWR) measure cyanotoxins.

SLR is in the western San Joaquin Valley in CA and was created by the Bureau of Reclamation (Figure 1). It is the fifth largest reservoir in CA, the largest off-stream reservoir in the United States and is a key part of the State Water Project (SWP) and federal Central Valley Project (CVP) (United States Bureau of Reclamation, 2023). SLR is approximately 14-km from north to south and 8-km from west to east when full. The water level has an elevation height range of 105-165 meters and the reservoir can hold approximately 2.5 km^3 of water (United States Bureau of Reclamation, 2023). The SWP is a water storage and delivery system that delivers water to about 27 million Californians and 750,000 acres of farmland and business throughout the state (California DWR, 2022), while the CVP serves another 2.5 million people and delivers water to approximately 3 million acres of the state's farms (United States Bureau of Reclamation, 2023). Water from SLR also serves the Santa Clara Valley Water District in the Southern San Francisco Bay Area, serving 15 cities with over 2 million residents (Santa Clara Valley Water, 2023). Most SLR water inflow is from man-made aqueducts which are supplied by northern California rivers. This reservoir grants flexibility for both water projects since it allows for state and federal water storage when there is excess winter or spring flows from the Sacramento-San Joaquin Delta. SLR is also a popular destination for recreational fishing, boating, and swimming for locals.

Summers at SLR can see temperatures as high as 110°F (43°C) and winters as low as 32°F (0°C). The warm, low-pressure atmospheric conditions in the Central Valley brings cool ocean air from the Pacific Ocean that then produces strong wind and gust conditions that level off in the late afternoon. High winds tend to break apart thick mats of algae, limiting surface bloom formation. However, the high onshore winds at SLR mixes the water column leading to low stratification (Kraus et al., 2011), mobilizing deeper nutrients. These strong winds can lead to high temporal and spatial variability of blooms across the reservoir (Binding et al., 2018). Boat use closures are frequent due to high winds, which heavily impact monitoring within the reservoir. Algal blooms have been an increasing concern for SLR managers; the DWR has made multiple public announcements regarding dangerous toxin levels in recent years (DWR, 2022). SLR is a good candidate to evaluate chl-a as a proxy for cyanotoxin estimation based on the new WHO21 guideline values because of the well documented presence of cyanotoxins.

2.2 Toxin Monitoring Data

The DWR has conducted cyanotoxin monitoring at SLR since 2013. The DWR collects one surface water grab sample off the dock in SLR from Basalt Boat Launch or Dinosaur Point (dependent on road closures), and from a raw water tap from the upper intake of the Pacheco Pumping Plant (Figure 1). For this study, we used the surface water grab samples collected at Basalt Boat Launch to compare with our field data and SRS. While the DWR has collected cyanotoxins since 2013, the sampling was sparse (5-8 samples per year from 2013-2015). For our analysis, we used data from 2016-2022 due to the larger DWR dataset during these years and coincident with the launch of Sentinel-2 in mid-2015.

The DWR begins to officially sample when there is a bloom sighting by the local rangers or if there is a notification made by the public. Not all initial visits have any toxin levels that trigger an advisory warning when the sampling period begins. On average, across the period of study, advisories were triggered on the first to third visit – beginning around May and lasting through October of each year. Monitoring can extend past October and is usually conducted until cyanotoxin levels falls below caution levels for two consecutive testing dates. Microcystin has been the only cyanotoxin detected during the period of record, except for a detection of anatoxin-a and cylindrospermopsin in August of 2022.

The DWR prepares their water samples by ultrasonication, where samples are inverted for 60 seconds to mix, then a subset is removed for algal identification purposes. The remaining samples are then sonicated to release toxins and prepared for analyses. In 2019, samples were freeze-thawed instead of sonicated. Sonication recommenced in 2020 (CA DWR, 2023). Toxin detection is performed using Enzyme-Linked Immunosorbent Assay (ELISA) techniques (EPA, 2023). The DWR uses the microcystins/nodularins (ADDA) kit, which is designed to detect over 100 microcystin congeners identified to date (but cannot distinguish between congeners; EPA, 2022). Data can be obtained for the cyanotoxins measurements in SLR through contacting the DWR's O & M Environmental Assessment Branch.

2.2.3 Chl-a Field Data Collection

We conducted four chl-a sampling events that occurred on the same day as a S2 satellite overpass and occurred within ± three days of a DWR sampling event. Three of these trips were conducted during the 2021 bloom season when DWR performs regular monitoring (08/27/2021, 09/06/2021, and 09/23/2021). We added one field trip (05/01/2022) before the bloom season to characterize non-bloom conditions. The DWR began toxin monitoring five days earlier, on 04/25/2022 but found no toxins. The next DWR sampling event was not until 05/23/2022. Thus, for spring 2022 the match-up between DWR data and field and SRS S2 data was five days rather than three. A total of nine sampling events were attempted, but frequent reservoir closures due to high winds limited the number of match-up sampling events. Each sampling event started at approximately 9:30 am PST and concluded about 11 am PST to best match the time of mid-morning satellite overpasses (10:00 and 10:30 am PST for S3 and S2, respectively). Surface water samples were collected from a utility boat and stored in 1-L Nalgene bottles. The bottles were kept in a cooler filled with ice and then refrigerated until laboratory analysis. Water collection sites were marked using a handheld Trimble Geo-XT GNSS unit. For the first sampling event, we collected triplicate samples at each site. Following analysis of the first round of samples, subsequent sampling events collected duplicate samples based on low sample variance.

For each sampling date, we visited pre-established sampling locations that were approximately 1-km apart. Due to wind conditions, we were unable to revisit the same location with high geolocational precision. The average distance of each sampling event from the pre-established sampling location was 56-m with a standard deviation of 36.6. An extra site was added for the 05/01/2022 sampling event because we wanted to include another sample closer to the edge of the reservoir while it was still full.

2.2.4 Laboratory Analysis of Chl-a

The refrigerated water samples were filtered following the EPA's Standard Operating Procedure for Chlorophyll-a Sampling and Analysis (Environmental Protection Agency, 2013). All samples were processed within 24 hours of collection and shaken in case of settling. Volumes of water filtered ranged from 50 – 500 mL based on water quality conditions using Whatman glass microfiber filter pads. An absorption spectrophotometer (Visible Spectrophotometer 721 LDC Digital Lab Spectrophotometer) measuring at 665 and 750 nanometers with a 90% acetone extraction solution was used for chl-a measurement following standard methods (APHA, 2005).

2.2.5 Remotely Sensed Data

2.2.5.1 Chl-a Products from Sentinel-2

S2 level-1C (L1C) top of atmosphere (TOA) reflectance products from 01/01/2016 to 12/31/2022 that provided coverage for SLR (tile 10SFG) were downloaded from the ESA Copernicus online database. We filtered 10SFG images for less than 25% cloud cover and visually inspected each image to further ensure cloud-free conditions over the reservoir. This resulted in a S2 dataset of 377 images.

Because of the absorption and scattering of light in the atmosphere, coupled with the overall low signal of water in SRS, atmospheric correction is crucial for water quality monitoring and assessment (Mobley et al., 2016; Seegers et al., 2021). The TOA data obtained from Copernicus were converted to aquatic remote sensing reflectance (Rrs) using ACOLITE version 20220222.0 software package (Vanhellemont and Ruddick, 2018). ACOLITE is an open-source software developed for aquatic applications. It applies the dark spectrum fitting method (DSF) for atmospheric correction, which determines the reflectance based on multiple dark targets in the image (Vanhellemont and Ruddick, 2018). This processor has been shown to be more effective for aquatic inland applications for S2 compared to other existing algorithms (Vanhellemont, 2019) and has been used in other inland aquatic studies (Bramich et al., 2019; Rodríguez-Benito et al., 2020; Theenathayalan et al., 2022), including in California (Lee et al. 2021). Images were resampled to 20-meters and the default sunglint correction was applied.

We selected three commonly used chl-a algorithms shown to work well for inland waters: Mishra and Mishra (2012), Gons et al. (2002), and Moses et al. (2012). Mishra and Mishra (2012) use bands 4 and 5. Gons et al. (2002) uses bands 4 and 7 (with central wavelengths of approximately 665 and 780-nm, respectively) and the additional option ACOLITE provides by switching band 7 with band 6 (approximate central wavelength of 740-nm). Moses et al. (2012) is a 3-band model using bands 4, 5 (approximate central wavelength of 705-nm) and 7, with again the addition of switching band 7 with 6. For the Gons et al. (2012), Mishra and Mishra (2012), and Moses et al. (2012) algorithms, we used the published coefficients in our implementation.

Our criteria to consider a match-up for S2 images and DWR sampling is that both must be acquired on the same day. This resulted in a total of 38 S2 images that had a match-up with DWR for further comparison. While 38 out of 377 represents only 10% of available images, we limited the time frame for S2 and DWR data comparison for the same day because varying winds can lead to different bloom spatial variability, which could have influenced the results.

2.2.5.2. Cyanobacteria cell counts from Sentinel-3

Remote sensing-based cyanobacteria cell count products were obtained from the Cyanobacteria Assessment Network (CyAN), a collaborative project between the EPA, National Aeronautics and Space Administration (NASA), National Oceanic and Atmospheric Administration, and the United States Geological Survey. The CyAN products, CI_{cyano}, are based on the Cyanobacteria Index (CI) (Wynne et al., 2008), and modified by Lunetta et al. (2015). CyAN offers daily and 7-day maximum value composite CI_{cyano} products in GEOTIFF format. The daily product was used for this study. The CI data were produced from ESA's Envisat's MERIS (2002-2012) and Sentinel-3 OLCI (2016-present) satellite data. The NASA Ocean Biology Processing Group converted OLCI's Level-1B data to Level-3 Rayleigh-corrected reflectance, masking clouds and sunglint. Their output products have a land and mixed land-water mask. Data were downloaded from NASA's Ocean Color's CyAN File search for 2016-2022 on 01/15/2023 (https://oceandata.sci.gsfc.nasa.gov/api/cyan_file_search). We converted the downloaded data products from digital numbers to CI following Eq 1 (Lunetta et al., 2015; Wynne et al., 2008) and finally to cyanobacteria abundance following Eq 2 (Lunetta et al., 2015). Note that Eq 2 is the general estimate of cyanobacterial abundance, however CyAN's converted range is limited from ~10,000-7,000,000 cells/mL. From the S3 time series, we selected images over SLR that were acquired on the same day that a DWR sampling event occurred, resulting in 71 images.

$$CI_{cyano} = 10^{(3.0/(250.0*\text{Digital Number})-4.2)} \tag{1}$$

$$\text{Cyanobacteria Abundance cells/mL} = CI_{cyano} * 1E{+}08 \tag{2}$$

2.2.5.3 Data Extraction and Time Series Development

We extracted the pixel values corresponding to our field sampling locations from the S2 chl-a and S3 cell count maps using the R raster package (R package version 3.5-15, Hijmans, 2022). For S2, the mean value in a 6 x 6 window (120-m) centered on the geolocation of each field sampling locations was extracted for each of the match-up dates in the time series. This spatial buffer was selected following a semi-variogram-based sensitivity analysis and follows findings from Sharp et al. (2021) who showed that critical scales of cyanobacterial blooms range from 70-175-m in a similar system (Clear Lake, CA). We did not incorporate any spatial buffer to the extraction of pixel values from the S3 maps since the pixel size is 300-m. These extractions were then used to create a time series of SRS-based chl-a and cyanobacteria abundance that could be compared against the DWR cyanotoxin monitoring data. Given the variability in geolocation for sampling stations between each field date, a different set of extractions was performed for each image date, with the window centered on the geolocation of the sampling station for that respective field date.

2.2.6 Data Analysis

To determine the agreement between the advisories suggested by the WHO and the DWR recreational health advisory levels, we created confusion matrices where a conceptual representation of the methods is shown in Figure 2.

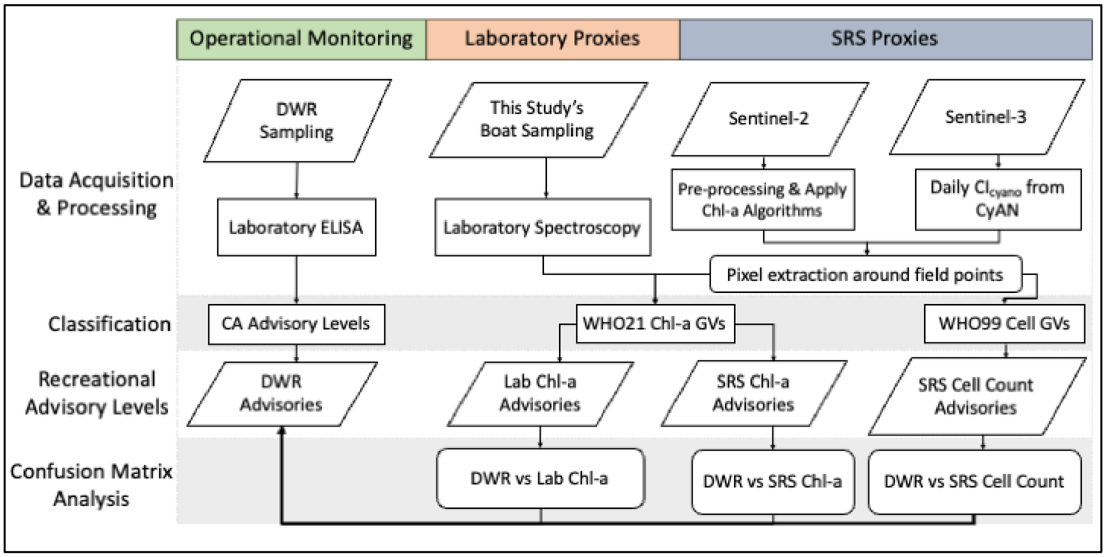

Figure 2-2. A representation of the approach used to examine agreement through confusion matrices between the California Department of Water Resources cyanotoxin advisories and laboratory/SRS chl-a and cyanobacteria classified by WHO GVs.

2.2.6.1. DWR vs S2 chl-a or lab chl-a

First, we classified the chl-a data from both the field campaign and S2 into two categories: no alert (Chl-a ≤ 24 µg/L) or elevated alert (Chl-a ≥ 24 µg/L) based on the WHO21 Alert Level 2 GVs for recreational waters (Table 1). We then classified the DWR advisories at the "warning" or "danger" level as "elevated alerts". When DWR issued "caution" advisories, or when no advisory was issued, we classified these as "no alert". There were no "caution" DWR advisories during our field campaign dates, however there were cautions present for both S2 and S3 dates. The DWR and WHO21 classes were then compared in a confusion matrix that tabulates how many observations agree and disagree per class.

2.2.6.2. DWR vs S3 cyanobacteria counts

The S3 cyanobacteria counts were classified using the WHO99 GVs (Table 1). WHO99 GVs of moderate or high probability of adverse health effects were classified as "elevated alert," and WHO99 GVs of relatively low probability were classified as "no alert". The classified data were then also compared with DWR advisories in a confusion matrix.

Table 2-1. The Guideline Values (GVs) for recreational waters by the WHO and advisories set by the Department of Water Resources (DWR) for cyanotoxins. Our classification for each guideline value for both agencies is defined in the table.

Authority	Authority Guideline Level	Quantity	SRS Guideline Value Classification
	Caution	0.8 - 5.99 µg/L Microcystins	No alert

CA DWR* (basis of comparison for this study)	Warning	6 - 19.99 µg/L Microcystins	Elevated Alert
	Danger	20 µg/L ≤ Microcystins	Elevated Alert
WHO (2021)	GV for Microcystins for recreational waters.	Chl-a ≤ 24 µg/L	No Alert
		Chl-a ≥ 24 µg/L	Elevated Alert
WHO (1999)	Relatively low probability of adverse health effects	≤ 20,000 cyanobacterial cells/ml *or* ≤ 10 chl-a µg/L	No Alert
	Moderate probability of adverse health effects	20,000-100,000 cyanobacterial cells/ml *or* 10.1 - 50 chl-a µg/L	Elevated Alert
	High probability of adverse health effects	≥ 100,000 cyanobacterial cells/ml *or* ≥ 50 chl-a µg/L	Elevated Alert
*Recreational health advisory levels. Note: US EPA finished drinking water 10-day health advisory for adults is 1.6 µg/L Microcystins, CA drinking water acute notification level is 3 µg/L Microcystins.			

2.2.6.3. Confusion matrix analysis

To quantify the level of agreement between lab/SRS advisories and DWR advisories, we calculated the total agreement (TA), false positive rate (FPR), and false negative rate (FNR) from the confusion matrices. TA is the proportion of observations that agree on the level of advisory from both methods (i.e., SRS triggers an alert when the DWR indicates an elevated advisory) (Eq 3). If both advisory approaches agreed for every match-up, the TA value would be 100%. A disagreement would result in either a false positive or a false negative. The False Positive Rate (FPR) (Eq 3) is the probability that a false alarm would be raised, which for this study means that an alert by either lab or SRS would be triggered when there is no alert by the DWR. The False Negative Rate (FNR), often known as the miss rate, is the probability that either lab or SRS would not trigger an alert while the DWR would issue one.

$$\text{Total Agreement (TA)} = \frac{True\ Positive + True\ Negative}{True\ Positive + False\ Positive + True\ Negative + True\ Negative} \quad (3)$$

$$\text{False Positive Rate} = \frac{False\ Positive}{False\ Positive + True\ Negative} \quad (4)$$

$$\text{False Negative Rate} = \frac{False\ Negative}{False\ Negative + True\ Positive} \quad (5)$$

2.3 Results

2.3.1 DWR Cyanotoxin monitoring

During the period of study, 41% of the DWR cyanotoxin monitoring visits resulted in “no advisory”, and 59% of the sampling visits resulted in some form of advisory (Figure 3).

The average duration of any triggered advisory (i.e., caution, warning, or danger) was 15.5 weeks for at least one site (Pacheco Pumping Plant and/or Dinosaur Point/Basalt Boat Launch). Warning or danger advisories for at least one site lasted an average duration of about 8 weeks, with high interannual variability. For example, in 2016 there were no consecutive warning or danger alerts, just two warning alerts for the year. However, sampling in 2016 was also minimal, with just seven visits for that year. The year with the greatest proportion of “danger” alerts was 2017, with about 20%, or 9 total alerts. The number of monitoring visits increased from 2016 to 2018; there were seven sampling visits for 2016, 29 in 2017, 19 in 2018, 32 in 2019, 26 in 2020, 29 in 2021 and 31 in 2022 (Figure 3).

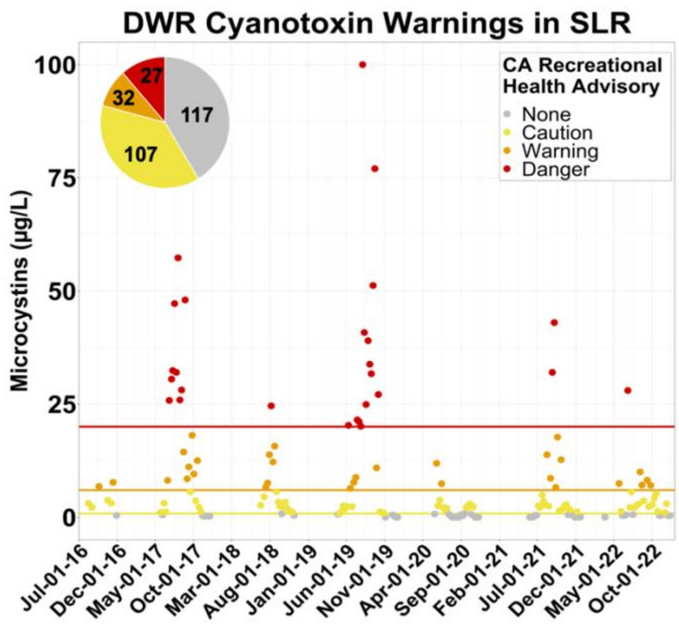

Figure 2-3. Microcystin samples collected from the CA DWR and determined via ELISA kits for 2016-2022 with indicated advisory levels.

2.3.2. Advisory comparisons

Table 2-2. The total agreement, false positive and negative rate of WHO GV classifications of laboratory chl-a, and SRS (chl-a and cyanobacteria) compared to DWR cyanotoxin advisories at San Luis Reservoir, CA.

Data Source	Product	False Positive	False Negative	Total Agreement
Field Campaign	Laboratory	10%	32%	74.3%
Sentinel-2 (20-m)	Mishra	12%	38.4%	78.9%
	Moses	80%	0%	51.5%
	Gons	45.8%	15.4%	67.6%

Sentinel-3 (300-m)	CyAN	12.2%	23.3%	83.1%

Table 2 summarizes the total agreement, false positive and false negative statistics. S3 had the highest TA (83%), followed by S2 (79%), and then the lab-based chl-a samples (74%). FPR and FNR were highly variable between the lab-based and SRS-based approaches (Table 2).

Lab chl-a-based advisories had a TA of 74% with DWR advisories (or non-advisories) (Table 2). Of all the methods, the lab-based advisories had the lowest FPR; in only 10% of the match-ups, lab-based chl-a measurements would have triggered an advisory while DWR monitoring did not. However, the lab samples had high FNR; in 32% of the match-up cases, DWR monitoring triggered an advisory where advisories from lab chl-a samples would not. The chl-a range measured from the field campaigns was 1.6-311 μg/L, with an average of 54.8 μg/L and standard deviation of 76.2 μg/L. The chl-a values, summary statistics, and coordinates of the centroids for each sampling site can be found in Table 2A-1 in supplementary materials. The date with the highest chl-a value was 09/06/2021 and the lowest value was from 05/01/2022. There was high spatial variability in chl-a measurements across the reservoir and across sampling dates (Figure 5). Across the four dates of field-collected samples for laboratory chl-a, about half would have triggered an advisory based on WHO21 (51%). From the three field dates in 2021 when SLR had higher bloom conditions, 68% of lab samples would have triggered a WHO21 advisory.

The TA between DWR and S2 advisories ranged from 51% to 79%, depending on algorithm used. The S2 chl-a algorithm that resulted in the highest TA was Mishra, followed by Gons and then Moses (Table 2). Moses had the highest FPR at 80% but had no false negative advisories. Gons and Moses's FPR were high (46% and 80% respectively). FNR for Gons and Mishra (15% and 38%, respectively) were similar or lower than lab chl-a-based advisories.

Of all proxies investigated, S3 had the highest overall TA: 83%. S3 FPR was similar to FPR values for lab and S2 Mishra. S3 had lower FNR than the lab samples, but S3 FNR was still higher than S2 Gons and S2 Moses. Of the 71 match-ups between S3 and DWR sampling events, there were 30 warning and danger DWR advisories, and in seven of these instances S3 resulted in no advisory. Figure 4 displays the confusion matrices of DWR alerts compared to alerts classified from lab-based chl-a samples, the best performing S2 algorithm, and S3.

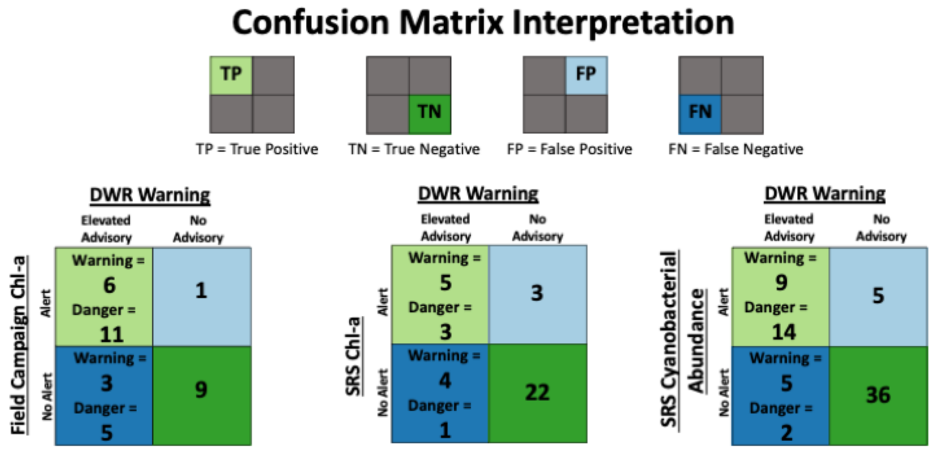

Figure 2-4. Confusion matrices comparing the field campaign samples, SRS Mishra, and CyAN to the advisory level determined by the DWR. SRS Mishra and CyAN are compared to the Basalt Boat Launch/Dinosaur Point location. The 05/01/2022 is not included since there was no DWR collection near that date.

There was high spatial variability within the reservoir across all proxy methods (Figure 5), indicating that a single advisory value does not apply to all areas. A spatial comparison of maps generated from S2, S3, and the field data shows that all proxy methods capture similar spatial patterns across the reservoir. Across the time series, northern portions of the reservoir tend to have fewer advisory conditions, whereas the middle-west portion (corresponding with sites 5 and 6) have the most frequent blooms. In general, areas of the reservoir where the lab chl-a indicated either an advisory or no advisory also match with SRS -based advisories, except for the September 23rd date. This exemplifies a case in which the S2 proxy indicates that the majority of the reservoir would be under advisory while the lab chl-a and S3 image showed regions where there would be no alert. The DWR did have an alert for SLR on this date. On 05/01/2022 there was no DWR alert, and all but one of the lab-based chl-a would not have triggered an advisory based on WHO21 GV. For 05/01/2022, S3 shows that most of the image had either no cyanobacteria present or levels too low to trigger any type of WHO99 alert. However, the S2 image indicates that large areas of the reservoir would not trigger an advisory apart from some small areas, especially in the southeastern part of the reservoir where S3 also had a few pixels indicating an alert.

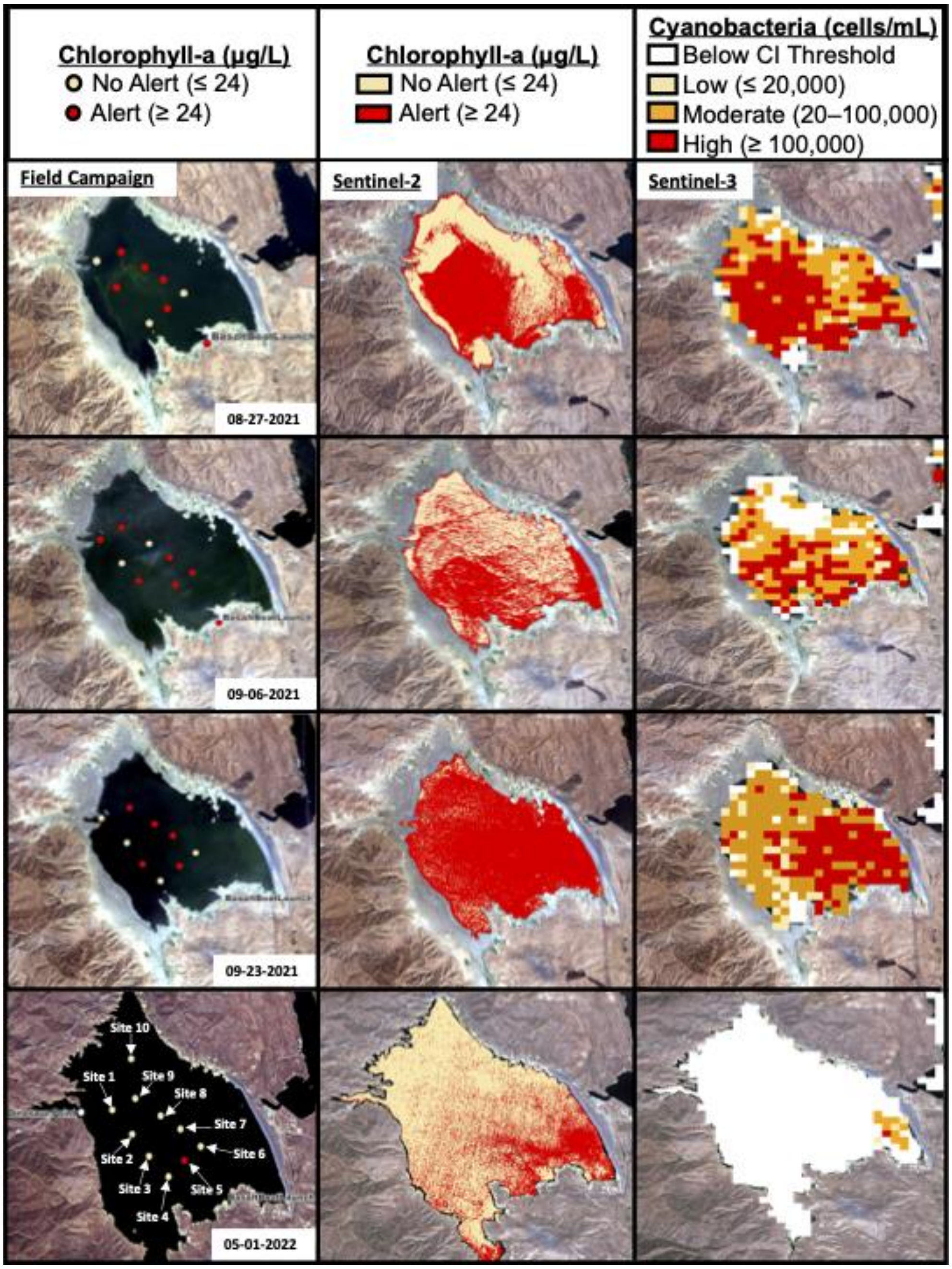

Figure 2-5. Left: field chl-a campaign points and DWR cyanotoxins color-coded based on WHO21 GVs. Middle: S2 (Mishra)-based WHO21 GVs. Right: S3 (CyAN)-based WHO99 GVs where white pixels represent CI detection below threshold limits. For the purposes of this study the WHO99 GV of moderate and high were collapsed into a single class of alert.

2.3.3 SRS and DWR Time Series

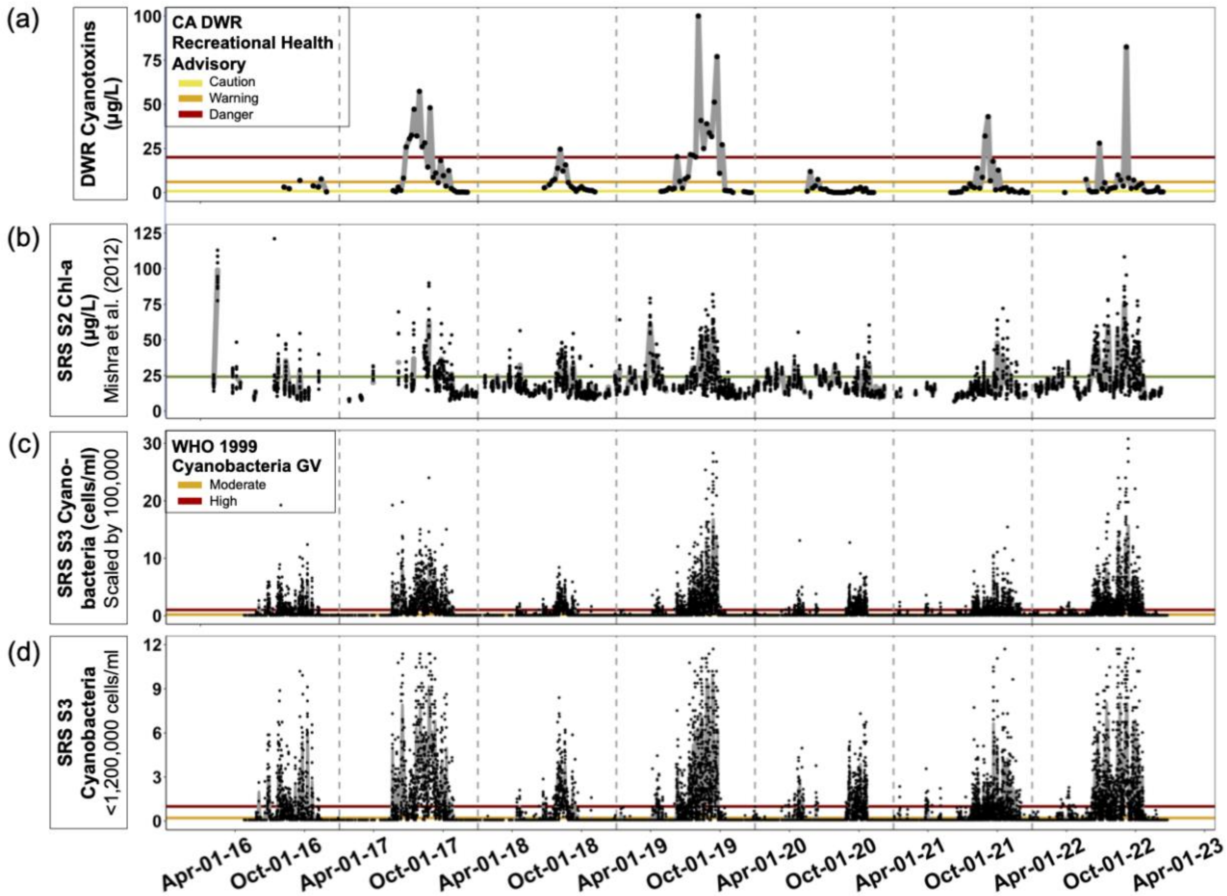

Figure 2-6. Dashed vertical lines indicate the beginning of a calendar year. (a) Cyanotoxins measured by the CA DWR with the state's recreational health advisory levels indicated by the horizontal lines. (b) Chl-a derived from Sentinel-2 using the Mishra et al. (2012) algorithm with the WHO21 recreational waters advisory value of 24 µg/L depicted as a green horizontal line. Chl-a y-axis limits are up to 125 µg/L, removing 5 outlier points. (c) Cyanobacteria abundance from Sentinel-3 with the WHO99 GVs on the horizontal scaled by 100,000. (d) Cyanobacteria abundance (from Sentinel-3) scaled on the y-axis for levels <1,000,000 cells/ml. Points for all graphs are the spatial mean of the day based on locations of field samples.

Figure 6 visualizes the time series of cyanotoxins, chl-a and cyanobacterial cell abundance over the period of the study. The figure highlights the temporal correspondence of DWR-based cyanotoxin values with proxy values from S2 and S3 as well as the temporal density of SRS-based proxies, particularly Sentinel 3. The DWR sampling campaigns occur when cyanotoxins are expected to spike soon and finish when values fall below caution (Figure 6a). The greatest cyanotoxin values occur around July-September and the values tend to fall below caution around late October-December. While DWR monitoring is strategically conducted during peak algal blooms seasons, it is evident that the absence of sampling during the remainder of the year may potentially miss conditions that would trigger an advisory.

The time series shows that the S2 chl-a (Mishra) results are mostly temporally concurrent with the DWR cyanotoxin time series (Figure 6b). The greatest chl-a values for S2 can be seen typically in July-August (Figure 6b), which is summer in California and typical for algal bloom trends. The lower S2 chl-a values where a WHO21 alert would be triggered generally ranges from October-April (Figure 6b). Much like the summarized in Table 2, there is agreement between the times when there were DWR danger levels and SRS chl-a values greater than 24 µg/L. Notably, there were times when SRS-based chl-a exceeded 24 µg/L, but there were no cyanotoxin data collected. While DWR cyanotoxin results tend to trigger some form of advisory in May, S2 chl-a exceeds 24 µg/L as early as February for all years. The S2 A/B satellites have a combined revisit time of 5 days, however, there are tiles that are excluded from the time series due to cloud, smoke or missing data within the images, which create data gaps in some parts of the year (Figure 6b). This is especially evident around December-April, which is winter and early spring in California when cloud cover and precipitation is higher.

S3 provides the most temporally dense time series since it has a daily revisit time. It is to be expected that S3 corresponds closely to DWR’s findings since cyanotoxins ultimately originate from cyanobacteria. However, we found that S3 had at least a moderate cyanobacteria abundance level starting in April, which is before the DWR typically samples.

2.4 Discussion

This study sought to evaluate the utility of SRS for cyanotoxin health advisories using SLR, a major multi-use reservoir in California, as a case study. This study found high rates of total agreement between public health advisories for cyanotoxin exposure in recreational waters issued by the CA DWR and proxy methods from both lab-based chl-a measurements and SRS. Over the period of study there were 71 match-ups between DWR cyanotoxin monitoring and S3, 38 match-ups with S2, and 4 match-ups with field sampling. With a total agreement of 83% for S3 and 79% for S2, SRS has good potential for augmenting cyanotoxin monitoring at SLR.

While the rate of false positives for S3 was low, S3 missed nearly one quarter (23%) of public health advisories that the DWR issued. However, these rates of false negatives may not solely be due to erroneous measurements by SRS, but rather spatial mismatch in sampling. With a 300-meter spatial resolution, S3 may have difficulty resolving nearshore point sampling conducted by the DWR. The DWR’s sampling is conducted off a dock (Basalt Boat Launch or Dinosaur Point; Figure 1), and there were multiple instances where a pixel was masked by CyAN because of its proximity to pixels classified as land (dock or shoreline). Thus, the closest available pixel may not represent the DWR sampling location or measurement. Furthermore, as visualized in Figure 5, there are many cases in which bloom conditions were present in some portions of the reservoir, but not necessarily at the locations of point-based sampling. The greatest advantage of using S3 for cyanotoxin warnings is its ability to directly approximate cyanobacteria abundance due to the position of its spectral channels as well as the near daily data it provides. Nonetheless, the 300-m pixel resolution limits the ability to resolve the spatial dynamics of cyanoHABS and precludes similar applications in smaller water bodies (Schaeffer et al., 2022 and Coffer et al., 2021).

Encouragingly, S2 also had high rates of total agreement with DWR advisories; with a 20-m pixel resolution, the sensor is ideal for enhancing monitoring in smaller inland water bodies impacted by cyanoHABs. While S2 spatial capabilities are better than S3, the 5-day revisit time is less ideal for water quality measurements since they can vary day to day. However, when combined with DWR measurements, the sampling frequency for SLR would be about every 3 days. Despite this, cloud cover remains a persistent issue for both sensors. While S2 does not have the spectral capability of detecting cyanobacteria, other studies have also suggested the use of both, given what is known about the high correlation with chl-a concentration and cyanotoxins (Rodríguez-Benito et al., 2020; Kislik et al., 2022). Rodríguez-Benito et al. (2020) proposed the use of S3 as an operational surveillance mode at mesoscale and then, when there is a positive chl-a detection, they suggested implementing S2 to locate the areas of bloom. While their paper focused on chl-a only, the same idea could be used in the case for cyanotoxin monitoring to inform and augment DWR monitoring efforts, whereby S3 could be used to detect high concentrations of cyanobacteria cells on a near-daily basis and the higher spatial resolution of S2 could be used to help inform the timing and location of DWR sampling efforts, potentially issue earlier warnings while awaiting lab results, and targeting warnings to certain recreational areas most likely to be impacted by the bloom. While the spatially limited sampling locations for DWR is understandable due to financial, time and access constraints, it is still very likely that during times the DWR collects no or low levels of cyanotoxins from their sampling stations, there are other areas of SLR that may harbor conditions warranting an advisory. With the short time period between overpass and CyAN products available, S3 can be easily integrated in the DWR sampling plans. S2 has images available the day after overpass; however, there are no operational chl-a products suitable for inland waters available yet, and further development would be needed to operationally support a monitoring program.

The time series of different cyanoHAB proxy indicators (Figure 6) further indicates the utility of SRS in augmenting or complementing routine toxin monitoring. Overall, we observed that peaks in chl-a concentration and high cyanobacteria cell abundance levels measured by SRS coincide with periods when DWR has confirmed cyanotoxin presence. However, SRS provides data at a regular sampling interval that occurs year-round, whereas the current DWR program typically samples between May-October, during “bloom” season, which results in substantially fewer observations and alerts. In some years, such as early 2018 and 2020, SRS indicated that possible recreational advisories were occurring before DWR monitoring commenced for the season. Thus, while SRS also does not provide a complete time series due to cloud cover (which has a winter seasonal bias in this system), it can still be used to supplement cyanoHAB monitoring, particularly when and where field sampling is not occurring. While some out-of-season alerts may be due to overprediction errors, some may also be due to real bloom occurrences that were not observed and reported to DWR to commence monitoring due to their location on the reservoir.

2.4.1 S2 Chl-a Algorithm Impacts

The choice of chl-a algorithm had a substantial impact on the total agreement as well as rates of false positives and false negatives. We would recommend the use of Mishra for San Luis Reservoir to augment cyanotoxin monitoring efforts based on the highest total agreement and lowest rate of false positive. However, further investigation in testing different algorithms, or the same algorithms used in our study, with more field data would strengthen these recommendations. Underestimation of chl-a is a well-documented challenge for SRS of inland waters that have high chl-a concentrations. The Mishra (2012) algorithm was originally developed with in-situ chl-a values ranging from 0.9-28.2 μg/L. Bramich et al. (2019) found that using the Normalized Difference Chlorophyll Index (NDCI), which is what the Mishra algorithm is built upon, underestimated chl-a measurements especially when samples were greater than 30 μg/L. Recently, Tóth et al. (2021) used ACOLITE and tested the Gons, Mishra, and Moses algorithms on S2 satellite data and found that SRS data overestimated chl-a if it was low (< 10 μg/L) and underestimated chl-a if it was too high (values ranged up to 653 μg/L). Algorithms such as Mishra specifically use formulations that combine reflectance data measured in both the red and near-infrared portions to be more robust to confounding water quality factors such as CDOM and other non-algal particulate matter such as suspended sediments that contribute to the overall turbidity of the water. Despite this, others have also reported that these algorithms using this band to tend to overestimate chl-a for low values (~ 5 μg/L) (Werther et al., 2022; Pahlevan et al., 2020).

Another possible explanation for when S2 chl-a algorithms under-predicted public health advisories may be due to the 2021 WHO GV’s new threshold reasoning for chl-a. The second edition “Toxic Cyanobacteria in Water” states that the value for chl-a is much more conservative compared to the WHO99 GVs. They also state that in most field scenarios, cyanotoxin levels should be lower than given by the GV. They comment that local areas that understand their cyanobacterial population should set their own alerts. While California’s DWR set their own advisory levels, they have used the previous WHO99 GVs as the reference for their warning and danger level. Whether it is more consequential to under or overpredict advisories should be weighed: the WHO21 GVs err on the side of lower chl-a threshold values to ensure that blooms are not underestimated.

The WHO21 framework supports parameters that are more locally or nationally accessible for cyanoHABs proxies. Along with chl-a, they have also recommended parameters such as Secchi disk depth or turbidity, two popularly measured water clarity indicators, as proxies for cyanoHABs (Chorus and Welker, 2021). Turbidity has been measured successfully through satellite remote sensing for decades (Moore, 1980; Choubey, 1992; Nechad et al., 2009; Dogliotti et al., 2015). While this study only focused on chl-a and CIs as proxies, future research could also investigate the utility of SRS-based turbidity for recreational alerts, and potentially a combined alert system that leverages both SRS-based chl-a and turbidity.

2.4.2 Consequences of False Negative and False Positive Public Health Advisories

While a high total agreement is the most ideal in the analysis, the performance of these proxies in terms of false negative and false positive advisories has consequences on information for the public to protect health and safety. A proxy method for cyanoHAB advisories that tends to overpredict blooms would maintain a conservative approach that prioritizes public safety. However, imposing multiple reservoir closures when there are no actual cyanoHAB events could lead to incurred costs for unnecessary water treatment or pumping interventions, fishing license and tourism revenue loss and general inconvenience to local and visiting recreational users (Wolf et al., 2017). CyanoHAB presence and cyanoHAB advisories can lead to millions of dollars in lost revenue annually for states that rely on tourism and recreation for revenue (Stroming et al., 2020; Hoagland et al., 2002). With high rates of false positive advisories, water managers may lose trust in monitoring technologies, and the community might lose trust in local and state authorities.

Unnecessary closures are not ideal and may incur costs, but those that become ill due to cyanoHAB exposure also incur a cost. There is limited literature and data on the financial cost of cyanoHAB-related illness, however DeFlorio-Barker et al. (2018) estimated the social cost of an individual to develop a gastrointestinal illness from a cyanoHAB to range from $10 to just over $300,000 in 2007 dollars. The lower value is based on typical over-the-counter medicine while the much higher price is associated with severe hospitalization. A follow up study by Stroming et al. (2020) adjusted this cost to exclude potential loss of life since cyanoHABs cannot be directly linked with death. Their new adjusted cost was $11 for mild, $264 for moderate, and $10,700 per person for severe gastrointestinal illnesses linked to cyanoHABs. Further, frequent failure to issue public health advisories in the presence of a cyanoHAB may also erode manager and public trust. Thus, while false positive advisories may have economic and perceptual consequences, favoring proxies that minimize false negatives would help prevent potential cyanoHAB related illnesses. In this study, the S2 Mishra chl-a algorithm had higher rates of total agreement relative to the Gons algorithm (79% and 68%, respectively). However, Gons had lowers rates of false negatives, while Mishra had lower rates of false positives. Which algorithm is selected for enhanced monitoring, and whether that is ultimately used to issue public advisories is dependent on what is considered is more important to the user, minimizing the potential for illness, or minimizing unnecessary costs and impacts to recreation.

2.4.3 Strengths and limitations of the study

SRS for cyanoHAB alerts provides spatially explicit mapping capability and additional monitoring throughout the year, inclusive of typical bloom seasons. Some of the disagreement between the SRS and DWR alert levels may be due to the high spatial variability of the blooms. Because of the strong winds, the spatial variability of blooms in this reservoir are high, meaning DWR samples collected from one side of the reservoir may not be indicative of the entire reservoir. Ultimately, the DWR samples are taken at only a few point locations at the shore of the reservoir (Figure 1) (and one from a tap), whereas S3 has 100s of pixels in the reservoir, and S2 has > 60,000 pixels measuring the reservoir. While the last day of our field campaign (05/01/2022) did have overall low values compared to the other dates, there was one sample that would have triggered an alert according to the WHO21 GV. As noted in our results, site five had high chl-a concentration, but there were no DWR toxin values for comparison. If there were DWR data for comparison, the sample would have been collected from a dock or at Pacheco Pumping Plant, which is on the opposite side of the reservoir from site five. From the S2 imagery shown in Figure 5, it is evident that these blooms form in different areas of the reservoir, where toxin sampling by the DWR would miss the event. This illustrates an important potential utility of remote sensing since it can measure areas where DWR does not, and during the times of the year they do not measure.

We have already seen great success with S3's CyAN products being used to reduce public exposure to cyanoHABs by guiding where to sample water quality and implement beach closures in states such as Utah, Wyoming, Oregon and New Jersey (Seegers et al., 2021; Schaeffer et al., 2018; WDEQ, 2019; OHA, 2019; NJDEP, 2020). The CyAN project has created an app that is the first of its kind to provide cyanoHAB data products to water quality managers for both recreational and drinking water sources in a cost-effective way (Schaeffer et al., 2018). In a recent study by Mishra et al. (2021) it was reported that data from CyAN had 84% bloom agreement detection across lakes from 11 states in the contiguous United States, a value remarkably similar to the findings from this study (83% overall agreement).

The current latency of water quality products is not always ideal for public health advisories, which are expected to represent the most up-to-date conditions. Field sampling and laboratory analysis of chl-a may be a reliable and simpler method than using SRS, however, it is also a slower process with smaller spatial coverage compared to using SRS. With field data, the time to collect samples and transport them back to a lab for analysis may take longer than using SRS data. ESA S2 images and NASA S3 CyAN products are available the next day of satellite overpass via their website (oceandata.sci.gsfc.nasa.gov/api). The availability of data is time sensitive for the issuance of public health advisories, so methods such as SRS that can provide quick and reliable measurements are necessary for enhancing monitoring.

2.5 Conclusion

The main takeaway from this research is that SRS can become an important tool for monitoring potential cyanotoxin exposures in cyanobacteria dominated lakes nationally or globally. This study assessed how well various proxies for public health advisories for cyanotoxin exposure agree with current government monitoring approaches. This study examined how well the recent WHO21 GVs work for using chl-a as a proxy for cyanotoxins and assessed the utility of SRS as a measurement modality for this proxy. The WHO21 GVs are relatively new and to the knowledge of the authors of this paper, have not been extensively explored in the context of SRS as of this study. Our results suggest that using SRS of chl-a is an acceptable proxy for predicting potential exposure to cyanotoxins from cyanoHABs. Our findings support previous research showing high rates of agreement between S3 and cyanoHABs. Further, we found that using the WHO21 GV was nearly as successful as using S3-based SRS based on the prior WHO99 GVs focused on cyanobacteria cell counts. Integrating SRS data with concurrent in-situ monitoring could create a cohesive time series for any lake such as San Luis Reservoir, an important instrument in California's water supply.

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2.8 Appendix

Site	**Latitude**	**Longitude**	**08/27 /2021**	**09/06/ 2021**	**09/23/ 2021**	**05/01/ 2022**	**Mean**	**Median**
1	37.067921°N	121.140481°W	15.7	41.5	16.7	2.3	19.1	16.2
2	37.059761°N	121.132072°W	148	20.7	17.4	3.9	47.5	19.05
3	37.053367°N	121.125202°W	-	189	37.1	3.5	76.5	20.1
4	37.046964°N	121.117744°W	23.5	-	17.8	6.9	16.1	17.8
5	37.051922°N	121.110261°W	61.9	311	26.4	68.7	117	65.3
6	37.056357°N	121.103118°W	22.5	47.1	24	10	25.9	23.3
7	37.061628°N	121.112120°W	27.1	42	42.1	4.3	28.9	34.6
8	37.065825°N	121.120100°W	233	10.1	64.5	3.1	77.7	37.3
9	37.071286°N	121.130662°W	236	103	34.9	2.0	94.0	69.0
10	37.082579°N	121.131882°W	-	-	-	1.6	-	-

Table 2A-1. Chlorophyll-a (µg/L) concentrations of all field sites collected with dates and coordinates. The latitude and longitude in the table are centroids of the four collection days (except for site 10 since that was done only on 05/01/2022).

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Chapter 3: Space-based Monitoring Enhances Public Health Alerts for Harmful Algal Blooms Across California

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Abstract: Monitoring cyanobacteria is crucial for assessing water quality, safeguarding public health, and understanding ecosystem dynamics impacted by harmful algal blooms. This study explores the potential of satellite remote sensing (SRS) to assess risks of cyanotoxin exposure in California's recreational waters, which have some of the highest microcystin levels globally, from 2016 to 2023. Utilizing SRS data, we compared cyanobacteria abundance in five lakes across California, with cyanotoxin advisories issued by the California Department of Water Resources (DWR). Analysis revealed SRS and DWR methods agreement ranged from overall agreement (OA) of 54% to 100% and balanced accuracies from 49% to 79%. Lake-specific assessments showed Lake Oroville with the highest OA (100%) and Pyramid Lake with the lowest (54%). SRS generally overpredicted alerts (false positive rate = 30%) and under-detected true positives (false negative rate = 42%), influenced by spatial variability and the nature of satellite detection versus point-based sampling. We found that sampling done in two different locations in San Luis Reservoir resulted in differing toxicity levels, likely influencing agreement rates. When doing a statewide cyanoHAB frequency assessment, six lakes showed no alerts, 56 lakes were below 10%, and nine lakes had alerts ranging from 11% to 25% above the WHO99 GV for recreational cyanobacteria. The remaining seven lakes exceeded 25%, with one nearing 100%, were primarily located in Southern California, often used for swimming and other recreation. Despite limitations in spatial resolution, SRS provides consistent, near real-time data essential for timely cyanotoxin risk assessments, complementing traditional in-situ sampling.

3.1 Introduction

Freshwater cyanobacteria occur naturally and play vital ecological roles as primary producers, nitrogen fixers, carbon sinks, and sources of oxygen (Bhardwag, et al. 2024; Demoulin, et al., 2019). Certain cyanobacteria species produce cyanotoxins, such as microcystins, anatoxins, cylindrospermopsin, and saxitoxins, which can pose risks to human health, animals, and the environment (Turner et al., 1990; Smayda, 1997; Carmichael et al., 2001; Metcalf et al., 2021). Cyanobacteria-dominated harmful algal blooms (cyanoHABs) can lead to overabundant biomass and toxin production, adversely affecting recreation, drinking water consumption, livestock watering, fisheries, and irrigation use (Landberg, 2002; Briand et al., 2003; Falconer and Humpage, 2005; Stewart et al., 2008; Backer et al., 2013). Additionally, cyanoHABs create economic burdens such as increased water treatment expenses, loss of water access, healthcare costs, and diminished recreational opportunities (Anderson et al., 2000; Bingham, 2015; Graham et al., 2016; Kouakou and Poder, 2019). CyanoHABs are a worldwide phenomenon (Paerl and Huisman, 2009; Brooks et al., 2016; Intergovernmental Panel on Climate Change; 2022) and the frequency and intensity of cyanoHABs are a concern for many water managers and communities because of eutrophication and global warming (Moss et al., 2011; Meerhoff et al., 2022).

A study found that in the United States (U.S) the spatial coverage of water quality monitoring is limited (Schaeffer et al., 2018). Around 90% of water bodies that sampled for water quality have less than five sampling stations, and ~50% have only one sampling station (Schaeffer et al., 2018). Satellite remote sensing (SRS) data can complement traditional in-situ water quality monitoring for cyanotoxins by providing vast temporal and spatial coverage of cyanobacteria (Wynne and Stumpf, 2015; Urquhart et al., 2017; Schaeffer et al., 2022), thereby expanding current monitoring programs (Schaeffer et al., 2015; Papenfus et al, 2020; Stroming et al, 2020). SRS cannot directly measure cyanotoxins (Stumpf et al., 2016). However, it has been used to identify areas where cyanotoxin concentrations are likely to be elevated based on the presence and density of cyanobacterial blooms (Kutser, 2009; Lunneta et al., 2015; Mishra et al., 2019). Integrating in-situ cyanotoxin measurements allow validation and calibration of SRS-based approaches, improving the accuracy and reliability of cyanotoxin monitoring efforts.

SRS can capture cyanoHAB variability throughout a lake, providing an understanding of cyanobacteria distribution and ensuring that remote areas are overlooked. California water bodies have some of the highest microcystin levels in the world, where in some cases it was >10,000 µg/L during bloom seasons (California Regional Water Quality Control Board, 2023). Spatial information is crucial because blooms often occur in areas not routinely tested. In Lopez Barreto et al. (2024), they found instances where blooms were more concentrated in areas compare to those that were being sampled, highlighting the importance of comprehensive monitoring.

The Department of Water Resources (DWR) manages California’s water resources, systems, and infrastructure, including the State Water Project (SWP) (California DWR, 2024). The DWR tests for cyanotoxins in their managed waters every year, however their testing is not year-round and has limited sampling locations due to cost and time constraints. In instances where cyanotoxins are detected within SWP water bodies, the DWR advises recreational users to exercise caution and refrain from any direct contact with algae (DWR, 2024). Recreational water activities may be restricted as a precautionary measure to safeguard public health if the algae are confirmed to be a harmful algal bloom (HAB). The DWR recreational health advisory levels are based on a risk assessment done by the Office of Environmental Health Hazard Assessment (OEHHA) using the best available science and while being public health conservative (California CyanoHAB Network, 2016). Recently, Lopez Barreto et al. (2024) classified cyanobacteria abundance derived from the Sentinel-3 (S3) satellites according to the World Health Organization’s 1999 guideline values (WHO99 GV) for cyanobacteria in recreational waters and compared them against cyanotoxin public health advisories issued by the DWR for San Luis Reservoir, a keystone reservoir in the SWP. They found an 83% agreement between SRS and DWR advisories, demonstrating the potential and utility for SRS to enhance monitoring efforts for harmful algal blooms.

This study assesses large scale regional risk of public recreational exposure to cyanotoxins by examining seven lakes distributed across California. This study tested the agreement between SRS and DWR advisories in an additional six lakes owned, managed, and monitored by the DWR, and tested the extensibility of the approach to a lake-level assessment. In the previous study, the cyanobacteria value used for comparison was from a pixel that was closest to the DWR sample collection site from their lake field sampling. However, using a single point to summarize the entire lake’s cyanotoxin level potential is not leveraging the true capability of SRS, and makes extension to unmonitored lakes challenging. Thus, in this study we used SRS to summarize cyanobacteria levels across the entire lake, then classified this value to the WHO99 GV. Our study includes San Luis Reservoir, the focus of Lopez et al. (2024), with the addition of six other California lakes of varying size and trophic status including Castaic Lake, Lake del Valle Lake Oroville, Perris Reservoir, and Pyramid Lake. We then classified all SRS-resolvable lakes in CA using the WHO99 GV and identified lakes with highest risk for public recreational exposure to cyanotoxins. With California’s diverse ecosystems, the findings from this study would be applicable to a great range of other local, regional, national, or even global systems.

Using SRS to create a lake-wide cyanoHAB summary allows us to capture locations that are not sampled by point-based measurements. This approach enables the collection of more comprehensive data than point-based sampling, potentially leading to discrepancies between SRS data and point-based samples. We believe SRS data based on the area closest to the collected reference cyanotoxin data would lead to a higher agreement. If there is a strong agreement for either or both methods, this will further support the use of SRS for cyanotoxin approximation.

3.2 Methods

3.2.1 Study Sites

The climates of Lake Oroville, San Luis Reservoir, Lake Del Valle, Pyramid Lake, Castaic Lake, Perris Reservoir, and Silverwood Lake exhibit distinct regional characteristics influenced by their diverse geographies. Lake Oroville and Lake del Valle experiences a Mediterranean climate with hot, dry summers and cool, wet winters (Ackerly et al., 2018; Houlton and Lund, 2018). San Luis Reservoir, situated in the semi-arid San Joaquin Valley, endures hot summers and mild winters, with most precipitation occurring during winter (Fernandez-Bou et al., 2022). Pyramid Lake and Castaic Lake, both in Southern California, share similar Mediterranean climates with hot, dry summers and mild, wet winters (Hall et al., 2018; Kalansky, et al., 2018). Perris Reservoir in Riverside County experiences a hot, dry climate with mild winters, typical of Southern California's inland regions (Hopkins, 2018). In contrast, Silverwood Lake, located in the higher elevations of the San Bernardino Mountains, enjoys cooler temperatures and higher precipitation, including occasional snowy winters and mild summers (Hopkins, 2018).

Figure 3-1. Map of the seven reservoir sites (names italicized) across California, US. Reservoir sizes are exaggerated for visualization purposes. The orange dots are large metropolitan Californian cities (in bold).

Our study sites include seven reservoirs of varying size and trophic status, all of which are part of California's SWP (Table 1 and 2). Two of the reservoirs are in Northern California, one in the Central Valley, and four in Southern California (Figure 1). While the primary purposes of these reservoirs are for water supply, flood risk reduction or hydroelectricity (U.S Army Corps of Engineers, 2024), all the reservoirs are commonly used for recreational activities, attracting residents and visitors for fishing, boating, swimming, hiking, and camping (California State Parks, 2024).

Table 3-1. Summary of the physical and geographic (Meyer et al., 2023; US Army Corps of Engineers National Inventory of Dams, 2024; Messager et al., 2016; CA DWR, 2024) reservoir metrics in this study in order from largest to smallest by area. Trophic level was determined by the most prevalent class for each lake from 2015-2019 by the Meyer et al. (2023) dataset.

Name	**Trophic Level**	**Capacity (Acre- Foot)**	**Area (Acres)**	**Volume (Acre-foot)**	**Mean depth (Meters)**	**Watershed Area (Kilometers^2)**	**Mean Residence Time (Days)**	**Primary Purpose**	**Other Purposes**	**Surface Elevation (Meters)**
Lake Oroville	Oligotrophic	3,537,577	15,805	49,587	1.0	9301	377	Flood risk reduction	Irrigation, recreation,	274.3
San Luis Reservoir	Eutrophic/ mixotrophi	2,041,000	13,000	48,139	1.1	213	59,577	Hydroelect ricity	Irrigation. Recreation	165.5
Castaic Lake	Oligotrophic	325,000	2,235	27.273	3.7	410	2056	Water supply	Irrigation and	467.9
Pyramid Lake	Eutrophic/ mixotrophi	180,000	1,360	4,252	1.0	744	602	Water supply	Recreation and	794.3
Perris Reservoir	Oligotrophic	131,452	2,340	10,320	0.6	22.6	17,700	Water Supply	Irrigation and	487.7
Lake Del Valle	Eutrophic/ mixotrophi	89,278	1,240	2,603	0.6	375	811	Water supply	Irrigation, recreation,	214.2

Silverwood Lake	Eutrophic/mixotrophic/o	78.000	990	4,711	1.5	82	1305	Water supply	Recreation, hydroelectri	1015

Table 3-2. Summary of the geographic coordinates, land characteristics and the averaged climate of our study. The primary national land class (NLCD) (U.S Multi-Resolution Land Characteristics Consortium), for both 2019 and 2021, and the California wildlife-habitat relationship (WHR), the vegetation type most important to wildlife (California Department of Forestry and Fire Protection, 2023), was summarized for each lake's Hydrologic Unit Code-8 sub-basin.

Name	**Latitude**	**Longitude**	**Distance to Nearest City (KM)**	**NLCD 2019 | 2021**	**WHR**	**Wind Speed (MPH)**	**Peak Gust Speed (MPH)**	**Air Temperature (°F)**	**Rain (inches)**
Lake Oroville	39.543	-121.491	4.8	Cultivated Crops	Annual Grassland	7.84	12.1	63.4	23.3
San Luis Reservoir	37.033	-121.133	N/A	Cultivated Crops	Annual Grassland	6.44	13.2	64.8	6.09
Castaic Lake	34.527	-118.611	1.6	Scrub/Shrub	Mixed Chaparral	9.46	60.1	61.1	12.8
Pyramid Lake	34.644	-118.764	19.3	Scrub/Shrub	Mixed Chaparral	11.0	63.7	60.3	10.8
Perris Reservoir	33.858	-117.183	0.6	Scrub/Shrub	Urban	4.62	52.3	65.6	6.2

Lake Del Valle	37.614	-121.745	3.2	Scrub /Shrub | Grassland / Herbaceous	Urban	7.75	14.0	58.0	9.6
Silverwood Lake	34.304	-117.318	N/A	Scrub/Shrub	Desert Scrub	5.47	27.0	58.0	10.5

3.2.2 Cyanotoxin Validation Data

The SWP is a crucial water management system that plays a vital role in supplying water to California's urban and agricultural areas, supporting economic development, and ensuring environmental sustainability (Lund et al., 2010; U.S Bureau of Reclamation, 2023; California DWR, 2022). The primary purpose of the SWP is to transfer water from northern regions of the state to water-deficient central and southern regions of California. Since 1968 the Division of Operations and Maintenance (O&M), the Environmental Assessment Branch of the DWR, has overseen water quality monitoring for the SWP. Beginning around 2006, the DWR has conducted cyanotoxin monitoring across important and key reservoirs in the SWP (CA DWR, 2021).

DWR weekly cyanotoxin sampling typically begins from mid-April (spring) until late September/early October (late summer/early fall) which is the typical algal bloom season in California (California DWR, 2024). They will sample for cyanotoxins prior to the expected bloom season if there are algal bloom sightings by local rangers or if there is a report made by the public. If a test returns positive confirming cyanotoxins, the DWR will post these corresponding health advisories at the sampling facilities, reservoir, and park entrances, and online (DWR, 2024). Their routine weekly sampling will continue until toxin levels (Table 2) are below caution levels for two consecutive weeks. The DWR collects water samples at the surface, 1-meter depth and raw water tap samples from lower or upper intakes, depending on the site. Toxins are measured using laboratory assay conducted by a DWR subcontractor, Greenwater Laboratories using ADDA-ELISA kits. Microcystin has been the primary and dominating cyanotoxin detected for all lakes during the period of study. For this study, we used only surface and 1-meter water samples to compare against SRS data. We used DWR data from 2016 to 2023 because while there was earlier DWR data available, sampling was very sparse. A description of how they estimate cyanotoxins can be found in Lopez Barreto et al. (2024) or through DWR's O & M Environmental Assessment Branch.

3.2.3 Cyanobacteria Cell Counts from Sentinel-3

Cyanobacteria SRS products were obtained from the Cyanobacteria Assessment Network (CyAN), a collective project between several federal agencies (EPA, 2023). The cyanobacteria data, CI_{cyano} (CyAN, Schaeffer et al., 2015), is based on the modified Cyanobacteria Index (CI) (Wynne et al., 2008; Lunetta et al., 2015). The CI_{cyano} data for 2016 until present are from the European Space Agency's Sentinel-3 Ocean and Land Colour Instrument (OLCI). Quality control flags to indicate potential contamination from clouds, sun glint, shadows, and land adjacency effects are applied to the CyAN products (Wynne et al., 2018, Urquhart and Schaeffer, 2019; Schaeffer et al., 2022). We used daily data to best match the DWR sampling data.

We converted digital numbers to CI_{cyano} using Equation 1 (Lunetta et al., 2015; Wynne et al., 2008) to estimate cyanobacteria abundance (Equation 2) (Wynne et al., 2010; Lunetta et al., 2015).

$$CI_{cyano} = 10^{(Digital\ Number\ *\ 0.011714-4.1870866)} \quad (1)$$

$$\text{Cyanobacteria Abundance cells/mL} = CI_{cyano} * 1E + 08 \quad (2)$$

Lake shapefiles created for the OLCI sensors, intended for CyAN data (Urquhart and Schaeffer, 2019), were used as the boundaries for each lake. However, Lake del Valle and Silverwood Lake were not part of this dataset. Despite having more than three valid water pixels, a parameter for the OLCI lake shapefile (Schaeffer et al., 2022), CyAN data consistency was an issue for these lakes likely due to lake area, land adjacency effects, and possible mixed pixels. Consequently, both lakes were omitted from the final results. The limited results and a visual representation of the limited data for Lake del Valle and Silverwood Lake are provided in supplemental Table S1 and Figure S1 respectively. Data extractions were performed using the raster package in R software (version 3.6-26, Hijmans, 2022).

3.2.4 Using Closest Pixels for SRS Cyanotoxin Approximation

In this study, we are interested in assessing potential bloom spatial variability within other regions of the lake not captured by single SRS pixel estimations or in-situ grab samples. In Lopez Barreto et al. (2024), one SRS-pixel based on the closest water sample location from their field work was used to compare to the closest DWR cyanotoxin collected sample. This was acceptable as that pixel was located within lake limits and not along the lake edge where mixed pixel effects could impact SRS values. But georeferenced points that can be confirmed to be within the lakes edges during fluctuating lake levels were unavailable. To mitigate this, we used a 600-meter buffer around collection sample locations. This distance was chosen because with S3's pixel resolution of 300-meters, this would allow up to two pixels of data from the DWR sampling point. If only one pixel was used, there is a high likelihood of being invalid during dry/low lake level locations. The average was calculated from the buffer to create a point-based comparison against the DWR cyanotoxins.

3.2.5 Lake-wide Summarization and Data Extraction for the Time Series

To use SRS's capability of measuring entire lakes, especially for those with no in-situ sampling locations, we summarized the cyanobacteria abundance across the lakes to a single value by using the lake's median cyanobacterial abundance. This single value still captures potential spatial variability of cyanobacteria in the sites rather than single-point samples.

3.2.6 Comparing DWR Cyanotoxins With S3 Cyanobacteria Counts

The S3 cyanobacteria counts for each lake were classified into public health-relevant categories of alert using the WHO99 GVs (Table 2). WHO99 GVs of moderate or high probability (≥ 20,000 cells/ml) of adverse health effects were classified as an "alert" and WHO99 GVs of relatively low probability (< 20,000 cells/ml) were classified as "no alert". The alert categories were then compared to the DWR advisory categories (Table 2) for that same day. We set a threshold for cyanobacterial abundance of ~20,000 cells/ml. Because of the limited digital number range (0-255), the actual threshold was 19,642 cells/ml. Pixels that were at or above this threshold were given a "1", and those below a "0". While "caution" is an alert that is important for long-term cyanotoxin monitoring and may help prepare for future closures, the DWR advises users to not enter the water only under warning and danger levels. Because of this, we classified only the latter two higher classes as "alerts".

Table 3-3. Guideline Values (GVs) for recreational waters by the WHO for cyanobacteria and advisories levels set by the CA Department of Water Resources (DWR) for cyanotoxins.

Authority	**Authority Guideline Level**	**Value**	**Classification for this Study**
California Department of Water Resources Recreational Cyanotoxin Advisory Levels	Caution	0.8–5.99 μg/L Microcystins	No Alert
	Warning	6–19.99 μg/L Microcystins	Alert
	Danger	20 μg/L ≤ Microcystins	Alert
World Health Organization 1999 Guideline Values for Cyanobacteria in Freshwater	Relatively low probability of adverse health effects	≤ 20,000 cyanobacterial cells/ml or ≤10 chl-a μg/L	No Alert
	Moderate probability of adverse health effects	100,000 cyanobacterial cells/ml or 10.1–50 chl-a μg/L	Alert
	High probability of adverse health effects	≥100,000 cyanobacterial cells/ml or ≥50 chl-a μg/L	Alert

3.2.7 Contingency Table Analysis Agreement between DWR and SRS-based advisories

We compared the DWR cyanotoxins against S3 cyanobacteria abundance classified by the WHO99 GV. We performed a contingency table analysis and calculated the overall agreement (OA), false positive rate (FPR), and false negative rate (FNR) to compare SRS alerts and DWR advisories. OA is the sum of the true positive (TP) and true negative (TN) of observations that agree on the level of advisory from both methods (i.e., both SRS and DWR alert trigger) divided by all observations (Equation 3). A false positive (FP) or a false negative (FN) would be the result of a mismatched alert or advisory. The FPR (Equation 4) is the probability that a false alarm would be raised, which for this study means that an alert by SRS would be triggered when there is no alert by the DWR. The FNR, often known as the miss rate, is the probability that SRS would not trigger an alert while the DWR would (Equation 5). A higher FNR would mean SRS-cyanobacteria underpredicts the DWR advisories, while a high FPR means it overpredicts.

$$\text{Overall Agreement (OA)} = \frac{TP + TN}{TP + FP + TN + FN} \quad (3)$$

$$\text{False Positive Rate (FPR)} = \frac{FP}{FP + TN} \quad (4)$$

$$\text{False Negative Rate (FNR)} = \frac{FN}{FN + TP} \quad (5)$$

We also calculated sensitivity (SN), specificity (SP) and balanced accuracy (BA). SN (Equation 6), or the true positive rate, measures the proportion of actual positives correctly identified. SP (Equation 7), or the true negative rate, assesses the proportion of actual negatives correctly identified. BA (Equation 8), the average of SN and SP, provides a comprehensive measure for imbalanced classes since the total alert rate of the DWR is not evenly split.

$$\text{Sensitivity (SN)} = \frac{TP}{TP + FN} \quad (6)$$

$$\text{Specificity (SP)} = \frac{TN}{TN + FP} \quad (7)$$

$$\text{Balanced Accuracy (BA)} = \frac{SN + SP}{2} \quad (8)$$

3.2.8 WHO99 Alert Frequency Maps

In addition to calculating lake-wide alerts, we also visualized the spatial variability of blooms for the five DWR owned sites by creating pixel-by-pixel cyanoHAB alert frequency maps. We created maps of pixels that were classified as “alerts” following the WHO99 GV (Table 2) for the 2016 to 2023 to visualize how often a pixel was likely to be in exceedance of the WHO99 GV level (Equation 9).

$$\text{Pixel Alert Frequency (\%)} = \frac{\text{n of pixels above the WHO99 GV}}{\text{n of total images}} * 100 \quad (9)$$

3.2.9 Applying the WHO99 GVs Statewide

Using the same lake shapefile created for S3’s OLCI, we created a time series for 76 lakes and reservoirs in California, including those that the DWR does not own, manage nor sample for cyanotoxins. The lake median CI_{cyano} was converted to cyanobacteria abundance and classified as “alert” and “no alert” following the WHO99 GV (Table 2), as was done for our other five study lakes.

We excluded three lakes in our analysis. Lake Tahoe was omitted due to its extremely clear, dark waters (Wang et al., 2020) particularly in the nearshore (Pearson and Huntington, 2019). The Salton Sea and Mono Lake were removed due to their extensive and complicated hydrology and water quality history (Stine, 1991; Wiens et al., 1993; Holdren and Montaño, 2002; Cohen, 2009), which make SRS of cyanoHABs less reliable for those water bodies.

3.3 Results

3.3.1 DWR and S3 Agreement Results: Point-Based Comparison

Table 3-4. Results of overall agreement (OA), false positive rate (FPR), false negative rate (FNR), sensitivity (SN), specificity (SP) and balanced accuracy (BA) of cyanotoxin advisories set by the California DWR against WHO99 GV using SRS of S3 for each lake. The percentage of DWR samples that triggered an alert and the totals for each contingency analysis are shown. The true positive (TP), true negative (TN), false positive (FP) and false negatives (FN) are also given.

Name	**n**	**OA**	**FPR**	**FNR**	**SN**	**SP**	**BA**	**DWR Alert**	**TP**	**TN**	**FP**	**FN**
Lake Oroville	11	100%	0%	0%	-	100%	100%	0%	0	11	0	0
San Luis Reservoir	113	84%	15%	18%	82%	85%	84%	35%	32	63	11	7
Castaic Lake	56	88%	9%	100%	0%	91%	46%	3.6%	0	49	5	2
Pyramid Lake	218	56%	48%	13%	87%	52%	69%	11%	20	101	94	3
Perris Reservoir	164	77%	11%	73%	27%	89%	58%	18%	8	119	15	22
All Lakes	562	72%	36%	53%	64%	97%	80%	17%	60	343	125	34

Rates of OA between SRS-based advisories and DWR-based advisories using a point-based comparison from the DWR sampling site ranged between 56 to 100% and the BA was 46 to 100% (Table 4). When all samples for all lakes were pooled, OA was 72%, FPR was 27%, FNR was 36%, SN was 64%, SP was 97% and BA was 80%. A minority of the DWR sampling (17%) led to alert level advisories. Lake Oroville had a low sample size, however had an OA and BA of 100%. There were no alerts set by the DWR and SRS at Lake Oroville.

Following Oroville, Castaic Lake had the next highest OA, a low FPR/high SP but a FNR of 100% and SN of 0%. There were no alerts by the DWR for this lake, however SRS created five alerts leading to the high FNR/low SN. Perris Reservoir followed (OA = 77%) but had the second lowest BA due to the low FPR/high SP, and high FNR/low SN. Over 80% of the samples from Perris Reservoir were no alerts according to the DWR, however the few times it was an alert, SRS under-detected the alert. Pyramid Lake had the greatest sampling size but had the lowest OA across all lakes. It had the highest FPR across all the lakes, but conversely had one of the lowest FNR which is why it the BA was higher than two other lakes with a greater OA. Only
11% of the DWR samples were an alert level of advisory, however SRS greatly overpredicted the presented alerts.

3.3.2 DWR and S3 Agreement Results: Lake-wide comparison

Table 3-5. Results of the total agreement, false positive and false negative rate summarized lake-wide.

Name	**n**	**OA**	**FPR**	**FNR**	**SN**	**SP**	**BA**	**DWR Alert**	**TP**	**TN**	**FP**	**FN**
Lake Oroville	26	100%	0%	0%	-	100%	-	0%	0	26	0	0
San Luis Reservoir	146	73%	31%	17%	83%	69%	76%	32%	38	69	31	8
Castaic Lake	124	90%	9%	33%	67%	91%	79%	4%	4	107	11	2
Pyramid Lake	312	54%	49%	15%	85%	51%	68%	8%	22	145	141	4
Perris Reservoir	195	72%	13%	90%	10%	87%	49%	20%	4	136	20	35
All Lakes	803	69%	30%	42%	58%	70%	64%	15%	68	483	203	49

Table 5. Results of the total agreement, false positive and false negative rate summarized lake-wide.

The OA between SRS-based advisories and DWR-based advisories using the lake-wide approach ranged between 54 to 100% and BA was 49 to 79% (Table 5). The lake-wide method provided 200 additional samples over the point-based comparison. When all samples were pooled, OA was slightly lower compared to the point-based approach, but BA deceased by 16%. The highest OA was in Lake Oroville (100%), and the lowest OA was Pyramid Lake (54%). Castaic Lake was the only site to have a higher OA using lake-wide summaries versus point-based comparisons. Perris Reservoir OA decreased by 5%, Pyramid Lake by 2%, and San Luis Reservoir by 11%. Castaic Lake was the only site to have an increase for BA using this approach, while Lake Oroville was unchanged and the remaining decreased.

The remaining performance metrics had differing performances across most lakes. The FPR remained stable for all lakes, with only changes up to 2%, except for San Luis Reservoir. The SN and SP decreased by 6% and 27% respectively for all lakes. Pyramid Lake and San Luis Reservoir FNR were consistent. Castaic Lake's FNR vastly improved but was the only instance. Perris Reservoir's FNR increased by 17%, despite DWR alerts slightly increasing. SP for Castaic Lake, Lake Oroville. Perris Reservoir and Pyramid Lake remained stable, while San Luis Reservoir decreased by 16%. Castaic Lake was the only site to have SN increase using a lake-wide summary, San Luis Reservoir remained stable, and the remaining lakes all decreased.

3.3.3 WHO99 Pixel Alert Frequency Maps for DWR Sites

The alert frequency maps (Figure 2) provide a spatial visualization of all cyanobacteria classified to WHO99 GV alerts from 2016 to 2023 for the five DWR sites. The values represent the percentage of observations in the SRS time series that were classified as an alert.

The alert frequency values across all lakes range from 0 to 27%. San Luis Reservoir had the highest frequency of WHO99 GV alerts in the time series, with a maximum of 27% of the time. Other sites with a higher alert frequency were Perris Reservoir (maximum = 6.7%) and Pyramid Lake (maximum = 11.9%). The lakes with the overall lowest frequency of alerts were Castaic Lake (maximum = 1.5%) and Lake Oroville (maximum = 2%).

Castaic Lake and Perris Reservoir appear to have a spatially homogeneous distribution of cyanobacterial abundance above the WHO99 GV (Fig 2). San Luis Reservoir has the highest frequency of alerts and spatially, these instances do not occur in bays or other small clusters of areas with high values, but rather high frequency that is distributed throughout the lake. The greatest values appear to be on the east side of the lake. Pyramid lake appears to have denser alert rates towards the center of the lake and have lower values around the edges, which may be driving the lower OA values calculated for this site because the DWR sampling sites were all near the lake edge.

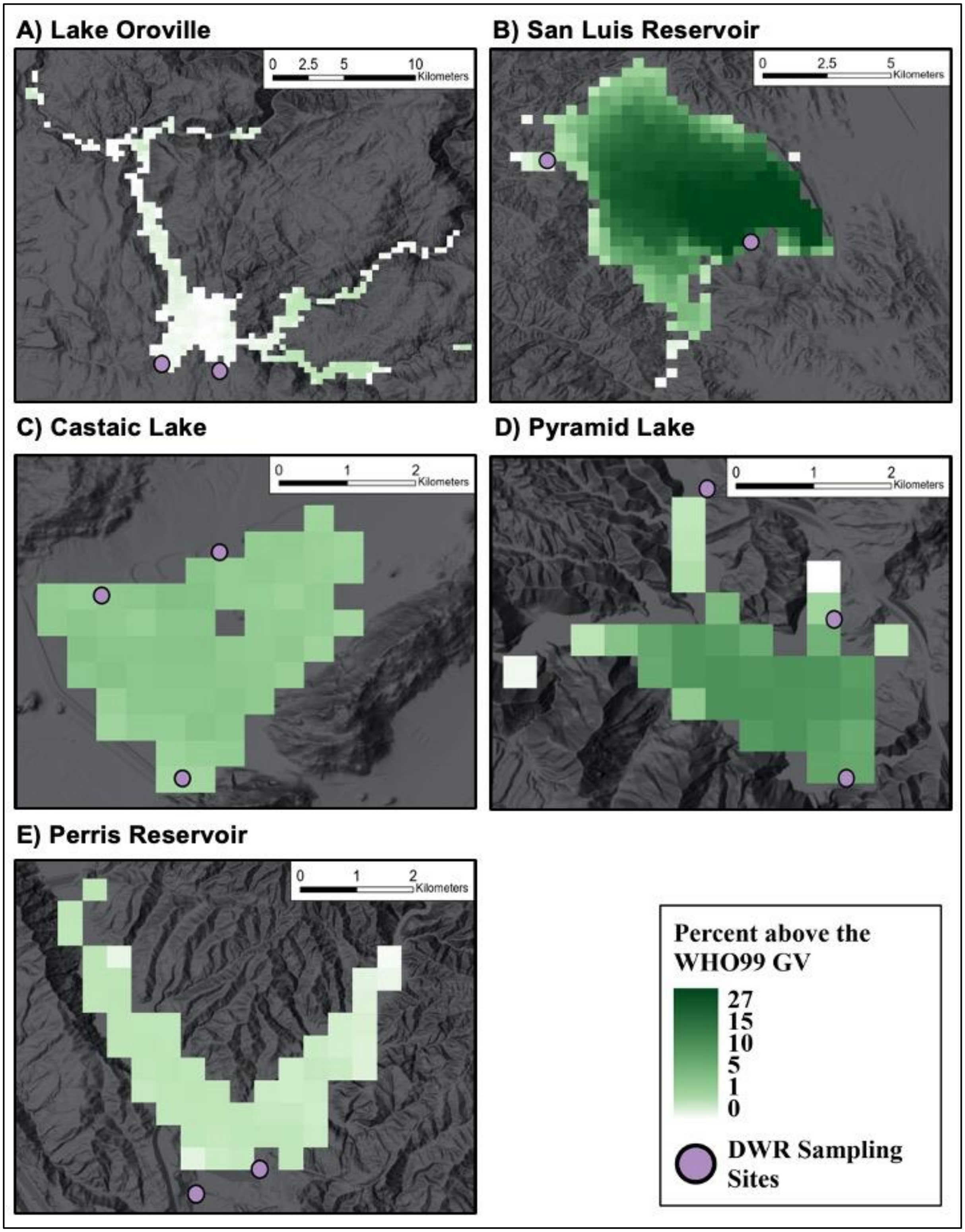

Figure 3-2. Frequency of alerts following WHO99GV from 2016-2023 for each study site. The DWR surface and 1-meter sampling locations are also shown.

3.3.4 WHO99 Alert Exceedance Frequency in California Lakes and Reservoirs

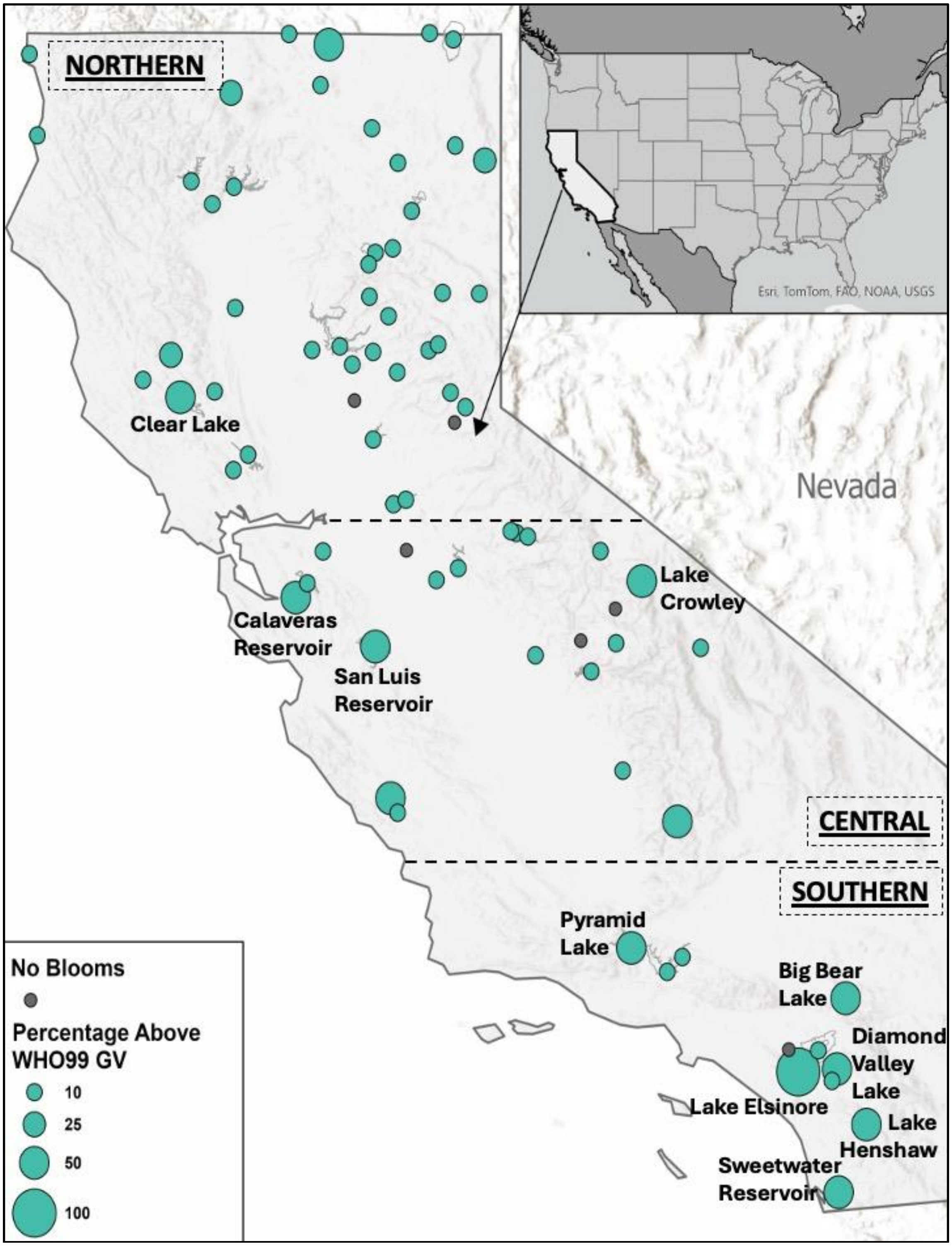

Figure 3-3. Map of the percentage above the WHO99 GV cyanotoxin risk for each lake resolvable by S3 in California divided into three regions (northern, central, and southern). The top ten lakes with great incidence of WHO99 exceedance are labeled.

Most lakes in California (58%) are found in the north, 28% in central, and 14% in the south (Fig 3). The six lakes with the greatest rates of a lake-wide median above the WHO99 GV were in southern California, three in central California, and one in northern California (Figure 3 and Table 5).

The ten lakes with the highest frequency of cyanobacteria alerts had a range of 18 to 99.3% between 2016 to 2023 according to SRS (Table 5). There were six lakes which had 0%, 54 lakes had a range of 0.05-10% and nine lakes had a range of 11-25% of alerts above the WHO99GV. The remaining seven lakes were above 25% of above the WHO99GV, where one site had a near 100%. The complete table of our statewide analysis can be found in Supplemental Table 2.

With SRS data there is almost daily data available for cyanobacteria (assuming there is no cloud or image disruptions), while there is limited in-situ cyanotoxin data available on the California State Water Board website (https://mywaterquality.ca.gov/habs/where/freshwater_events.html) for the top ten greatest cyanoHAB frequency lakes (Table 5). Clear Lake had the most data publicly available, over three times than the second greatest, while Calaveras Reservoir had no data available. Each lake's corresponding owner or managing agency and the total cyanotoxin data publicly available for each is provided by the from 2016 to 2023.

Table 3-6. Top ten lakes of 76 in California with frequently occurring WHO99 GV alerts as estimated from SRS data from 2016-2023, where 8 are not owned, managed, or sampled by the DWR. The total publicly available cyanoHAB toxin data available in the California Water Board data portal (https://mywaterquality.ca.gov/habs/where/freshwater_events.html) and cyanobacteria data available from CyAN from the time period.

Lake/Reservoir	**Frequency above WHO99**	**Owner/Managing Agency**	**California Data Portal Cyanotoxin Data (n)**	**SRS CyAN Data (n)**
Lake Elsinore	99.3	City of Lake Elsinore	22	1982
Lake Henshaw	43.4	Vista Irrigation District	8	1841
Calaveras Reservoir	32.8	San Francisco Public Utilities Commission	0	1719
Lake Crowley	29.7	Los Angeles Department of Water and Power	3	1803
Big Bear Lake	29.3	Big Bear Municipal Water District	41	1946

San Luis Reservoir	26.0	DWR	12	1979
Sweetwater Reservoir	25.3	Sweetwater Authority	2	1663
Diamond Valley Lake	25.0	Metropolitan Water District of Southern California	2	1795
Clear Lake	22.1	Yolo County Flood Control and Water Conservation District	142	2064
Pyramid Lake	18.0	DWR	9	1862

3.4 Discussion

3.4.1 Point-Based vs Lake-Wide Against DWR Cyanotoxins

One of the motivations of our paper is to use a metric that summarizes the conditions across a lake effectively. Comparing an alert that was classified using the lake-wide median against the DWR samples is comparing a summarized value from multiple locations to a point sample. Because of spatial differences, it is reasonable that the data closest to the validation site would have a greater overall agreement against a value that condenses cyanobacteria spatial variability to a single value.

Using a point-based comparison greatly outperformed a lake-wide according to the BA. The OA treats correct predictions and errors as equally important, whereas BA offers a more nuanced perspective by focusing specifically on true positives and true negatives. There is over six-times more DWR non-alerts than alerts, which could overestimate the true accuracy of using SRS for cyanotoxin monitoring. The BA helps interpret these unequal classes. We assumed that the lake-wide results would be similar to the point–based results, which was true, but we also expected them to have a lower agreement rate due to the nature of summarizing a large area to compare to a specific location. With the slightly lower OA using lake-wide summaries, we can conclude that it does not perform as well as a point-based comparison, but the decrease in OA is small but the BA had a greater decrease.

Using a lake-wide approach in a lake well known for its persistent and higher advisory levels may be more appropriate than using point-based collection/measurements. We found regions with SRS that may have had toxins, whereas the DWR sampled sites did not. Lake Oroville overall has low cyanobacteria alert values (Figure 2) which tracks with the outcomes of Table 3 where all DWR samples cyanotoxins did not trigger an alert. However, there may be locations in the lakes where alert level cyanoHABs may have occurred but were not being sampled by the DWR (Figure 2). Castaic Lake and Perris

Reservoir spatially homogeneous appearance (Figure 2) may be the result from high winds or other horizontal mixing processes. Frequent and high winds may influence bloom location, where when averaged over time, could lead to similar frequencies across the lake (Table 2) which would be missed if only relying on select point samples.

Contributing factors to the high FNR and false positive rate (FPR) include the concentration of algal blooms at lake edges, minimal DWR alerts relative to non-alerts, and the inability of SRS to explicitly detect cyanotoxins. The FNR was 42% for pooled samples using the lake-wide approach, which is 6% higher than using the point-based approach. With this metric, SRS underestimates/misses alerts 42% of the time. The FPR was 30%, meaning SRS overestimates DWR alerts 30% of the time. There is a total of 147 DWR alerts (15%) across all sites compared to the 683 non-alerts (85%). The quantity of alerts is not necessarily a small sample size, however distributed across five sites may not be enough to confidently state this high of an FNR. Another highly plausible explanation is that the cyanobacteria found in the lake may not be toxin-forming (O'Neil et al., 2012; Stumpf et al., 2016). SRS captures a cyanobacteria by detecting the associated pigments (phycocyanin) but cannot explicitly sense cyanotoxins because these harmful substances do not have distinct spectral signatures detectable by current remote sensing technologies.

3.4.2 Lakes and Reservoirs with High Cyanotoxin Risk

The ten lakes with the highest frequency of cyanoHAB alerts were mainly in southern California, followed by central and northern California. These results align with Urquhart et al. (2017), who found the greatest increase in total bloom area from 2008 to 2012 in central California, followed by southern California, with northern California showing the smallest increase. Our time series from 2016 to 2023 supports these trends, suggesting that bloom patterns have shifted over time. Northern California is colder and has higher rates of precipitation, central California has a mix of climates with hot inland summers, and southern California is warmer and drier. With limited precipitation, if lake levels become low then entering nutrients could become more concentrated compared to a fuller lake (Jeppesen et al., 2015; Özen et al., 2010; Brasil et al., 2016). Southern California, especially closer to the coast, has greater urban cover (U.S Census Bureau, 2020) which may influence the concentration, rate and type of nutrients entering the system (Müller et al., 2019; Walsh et al., 2015). While central California may not be as urban, it is still well known for its hot temperatures and agriculture which would also support high nutrient carrying runoff (Moss et al., 2013). Hotter temperatures and higher concentration of nutrients would greatly support algal growth which would explain our findings.

Despite being the lakes with the greatest cyanobacteria rates in the state, there was limited cyanotoxin data available found in the California State Water Board website. The lake with the highest WHO99 GVs frequency was Lake Elsinore, which has a documented history of HABs which is likely why it has one of the highest data samples available (Table 5). The Santa Ana Regional Water Quality Control Board samples various points around the lake and have a similar procedure as the DWR for their cyanotoxin monitoring (City of Lake Elsinore, 2024). Clear Lake has a similar monitoring plan in place (Big Valley Band of Pomo Indians, 2024). Lake Henshaw's agency states that they collect cyanotoxins weekly from two sites in the lake. The other lakes had some data available in the portal, except Calaveras Reservoir, where there was no cyanotoxin data readily available online. The monitoring schedule for Lake Crowley and Diamond Valley Lake was not readily available, however there have been previous news reports of danger warnings of detected cyanotoxins/HABs (California State Water Resources Control Board, 2021; Lassen County News, 2023; NBC Los Angeles, 2018; CBS News, 2024). Say something to emphasize the importance / utility of having a SRS dataset, especially with limited toxin data available.

Knowing where there are confirmed high rates of cyanobacteria (Figure 3), paired with cyanotoxin data (Table 6), can significantly enhance future cyanotoxin research. Having a list of lakes most affected by cyanobacterial blooms can be used to prioritize monitoring efforts and allocate resources more efficiently to these regions. Combining SRS cyanobacteria and in-situ cyanotoxin data, researchers can further improve the accuracy of bloom assessment and better understand the correlation between cyanobacteria presence and toxin production, improving predictive models and risk assessments.

3.4.3 Closing Spatial and Temporal Data Gaps

SRS provides substantially more consistent data for cyanobacteria compared to cyanotoxin samples collected by various agencies or managers (Table 5). SRS allows for standardized cyanobacteria retrieval with a higher revisit frequency, and the data is freely accessible the following day through CyAN. In contrast, cyanotoxin data are distributed across different agencies (Table 6), potentially using varying sample collection methods, and may not be publicly shared promptly. The total cyanotoxin data for San Luis Reservoir and Pyramid Lake available on the California State Water Board's website are much lower than the data used in this study, as obtained by personally inquiring with the DWR O&M branch. Furthermore, DWR initializes cyanotoxin sampling based on local reports and the duration of detected toxicity levels at sampling locations. SRS provides near real-time monitoring and trends of cyanobacterial bloom development, helping water managers determine the optimal timing for cyanotoxin testing during peak algal activity periods. Including SRS data in current monitoring plans can enhance the focus on both timing and location of potential cyanotoxin hotspots for targeted testing.

Cyanotoxin production in algal blooms is highly variable and depends on specific environmental conditions (Davis et al., 2009; Chorus and Bartram, 1999), meaning that cyanobacteria found in different areas of the same lake may not always produce toxins (Szlag et al., 2015). According to the DWR data, not all lakes are toxic such as Lake Oroville or (usually) Castaic Lake. While these lakes have little to no cyanotoxins found when sampled, the SRS data also align with these findings by indicating low recommended alerts during the sampling period. But there may be differing quantities or types of cyanobacteria occurring in the lake that may be different in the locations collected from the DWR. In Figure 2, Lake Oroville's DWR sampling points are in the lowest areas for alerts (< 0.05% alert exceedance), while the eastern side has greater frequency rates (2% alert exceedance) which may indicate larger cyanobacteria concentrations compared to current sampling. SRS can help water managers by providing detailed spatial and temporal data on algal bloom distributions, highlighting areas with high concentrations of cyanobacteria for targeted cyanotoxin testing.

SRS data can be used to support help monitoring efforts at lakes such as San Luis Reservoir because of its well documented toxicity and bloom spatial variability (Figure 2). Basalt Boat Launch (Figure 2B; south-west point) has over three times the data (n = 150) and double the alert rate (34%) that Dinosaur Point (Figure 2A; north-east point) has (n = 41 and alerts = 15%), which is where current and future cyanotoxin monitoring is being done because of road closures. This aligns with the pattern shown in the alert frequency maps (Figure 2), where areas close to Basalt Boat Launch have trends of higher WHO99 GV alerts, while the Dinosaur Point site has some of the lowest rates of the figure. Since we are attempting to summarize the cyanotoxin potential of the whole lake, the Dinosaur Point location may be underestimating the bloom status of further areas at San Luis Reservoir that can be found in the Basalt area.

3.4.4 Study Limitations

A disadvantage of using SRS for cyanobacteria detection or screening is the lower spatial resolution of the sensor used, which is 300-m resolution, potentially missing small-scale blooms and providing less detailed highly local information compared to in-situ data and has challenges in lakes that are characterized by complex shape. Other sensors like Sentinel-2, with a higher spatial resolution of 10-20 meters, can provide more detailed images of smaller blooms and water bodies of chlorophyll-a which has been used as a successful proxy of cyanotoxins (Lopez Barreto et al., 2024). NASA's Earth Surface Mineral Dust Source Investigation (EMIT) focuses on mapping surface minerals, but its technology could also be adapted for water quality applications (Jet Propulsion Laboratory, 2024). Future missions, such as and Surface Biology and Geology (SBG), specifically designed for terrestrial and aquatic environments, will provide high-resolution hyperspectral imaging allowing for detailed characterization of cyanobacteria pigments and better differentiation between bloom types (Cawse-Nicholson et al., 2021). This capability will improve detection accuracy and provide more comprehensive data for water quality management.

The WHO99GVs are only applicable to lakes that have confirmed cyanotoxins found in the system. SRS can accurately detect cyanobacteria presence and levels, however using the WHO99GV, we are assuming denser blooms are toxin-producing. Detected cyanobacteria presence does not ensure cyanotoxin exposure because not all cyanobacteria strains produce toxins (Chorus and Bartram, 1999; Chorus, 2001; Bláha et al., 2009; Szlag et al., 2015). The production of cyanotoxins is influenced by various environmental factors that can vary by site (Kaebernick and Neilan, 2001; Holland and Kinnear, 2013; Neilan et al., 2013; Boopathi and Ki, 2014). While cyanobacteria presence can signal potential risks, actual toxin levels must be measured directly to confirm exposure and assess health risks (Stumpf et al., 2016).

Pyramid Lake has a low FNR, meaning that SRS has a good rate of detection when it is potentially toxic. However, it had the lowest OA because it often overpredicts cyanotoxin risk. While this site's DWR alert frequency is relatively low (7.9%), presence of higher toxicity levels is not constant throughout the timeseries. In 2021, there were 19 DWR alerts compared to the previous and following year of only 3. In 2023 there were also only three DWR alerts, however the levels of cyanotoxins prompted wide news coverage (Rodriguez, 2023) and the DWR urged visitors to not enter the lake (DWR, 2023). This means that cyanobacteria in Pyramid Lake have confirmed cyanotoxins, however the sampling location may not be reflecting potential hotspots which appear to be the center of the lake according to Figure 2, or the algal bloom intensity may not be consistent over the time period. More sampling at different locations might be able to address the poor OA at Pyramid Lake. SRS could likely inform such monitoring, including the addition of sampling sites that align with areas of most frequently occurring alerts.

3.4.5 Additional Sources for Water Quality Data in California

There are other monitoring organizations that share similar and other water quality data like the DWR. Some noted are the Klamath Basin Monitoring Program, East Bay Regional Park District, Big Valley Band of Pomo Indians (Clear Lake focused), and Kern County Public Health. Some organizations' frequency, methods for sampling, or time frame are not the same as the DWR's. Many organizations give clear past and current water quality advisories concerning HABs, however the actual cyanotoxins data is not available alongside these notices. While the data may not be immediately available for download, the DWR and most agencies/collaborators/organizations do share their findings when inquired.

Several participating organizations contribute water quality information via CEDEN, the California Environmental Data Exchange Network. CEDEN represents a collaborative initiative across California's water and environmental sectors, welcoming federal, state, county, and private entities eager to share data statewide. Facilitating data exchange among diverse groups, the CEDEN network aims to provide public access to water and environmental data. CEDEN is a direct result of Assembly Bill 1755 (AB 1755), known as The Open and Transparent Water Data Act, which was signed into law in 2016. This bill directs the DWR, the California Water Quality Monitoring Council, the State Water Resources Control Board, and the California Department of Fish and Wildlife, to establish, manage, and sustain a comprehensive statewide integrated water data platform. The bill requires the development of a strategic plan outlining program implementation, as well as protocols for data sharing, documentation, quality control, public access, and the promotion of open-source platforms and decision support tools pertaining to water data (California Water Code Section 12400, 2016). If those that collect water quality data were to publish their data to this public repository, then this can support further collaboration, transparency and provide further informed decision-making for important sites.

3.5 Conclusions

Our study highlights the effectiveness of point-based cyanotoxin monitoring over lake-wide summaries, demonstrating a higher accuracy in detecting localized algal blooms and their associated risks. From our five study lakes, San Luis and Perris Reservoir produce the greatest rates of cyanotoxins according to the DWR data. The OA of these lakes for both point-based and lake-wide approaches yielded reasonable agreement (~70%). Lake Oroville and Castaic Lake had the lowest cyanotoxin alerts and had the highest OA across the study, suggesting SRS works best with lower cyanobacteria levels. The nuanced evaluation provided by balanced accuracy (BA) versus overall accuracy (OA) reveals that while lake-wide approaches offer a broader perspective, they often underestimate the true variability and potential hotspots within a lake. Further investigation should be done for using lake-wide summaries to compare point samples, such as having varied locations of in-situ samples. The increased spatial coverage provided by SRS ensures a more accurate representation of cyanobacteria distribution, thereby improving the overall monitoring and assessment of cyanoHABs in the lake. Overall SRS of cyanobacteria of inland lakes provide reasonable agreement but should have in-situ data to help establish a better comprehension of the toxicity rates of the lakes.

The spatial and temporal inconsistencies in cyanotoxin presence underscore the need for targeted, high-resolution monitoring strategies. In regions with higher cyanobacteria risk, such as Southern California, the integration of remote sensing data with traditional sampling methods can enhance monitoring precision and resource allocation. By identifying lakes with persistent and high advisory levels, we can prioritize these areas for more intensive study and intervention. Nine out of the ten lakes with the greatest WHO99 GV frequency had less than 50 cyanotoxin data publicly available through the official California HAB portal across eight years. These lakes are managed or owned by a variety of agencies, including DWR, and likely have more data collected for these lakes but may have not been disseminated to the data portal. The combination of satellite remote sensing (SRS) and in-situ data collection provides a robust framework for understanding cyanobacteria dynamics and mitigating their impacts.

3.6 Appendix

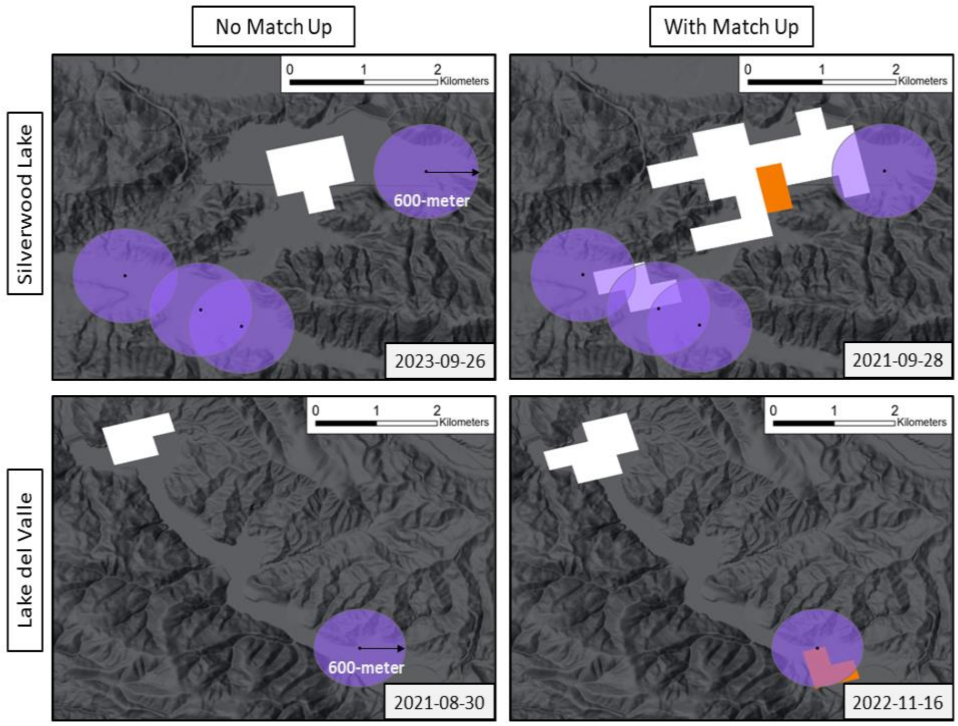

Figure 3A-1. Visual representation of the spatial limitations of narrower lakes using larger resolution satellites. On the left shows no data available using a 600-meter buffer around a sampling location while the right shows successful data retrieval with the same

Table 3A-1. The results of overall agreement (OA), false positive rate (FPR), false negative rate (FNR), sensitivity (SN), specificity (SP) and balanced accuracy (BA) of cyanotoxin advisories set by the California DWR against WHO99 GV using point-based SRS of S3 for the two lakes removed from the results of the study. The percentage of DWR samples that triggered an alert and the totals for each contingency analysis are shown.

Name	n	OA	FPR	FNR	SN	SP	BA	DWR Alert	TP	TN	FP	FN
Lake del Valle	0	-	-	-	-	-	-	-	-	-	-	-
Silverwood Lake	7	57%	50%	0%	100%	50%	75%	14%	1	3	3	0

Table 3A-2. All California lakes WHO99 GV frequency of alert exceedance as estimated from SRS data from 2016-2023, where 8 are not owned, managed, or sampled by the DWR.

ID	Lake Name	n	Frequency Above WHO99
1	Big Bear Lake	1946	29.29
2	Big Lagoon	1155	0.52

3	Black Butte Lake	1887	2.01
4	Bouquet Reservoir	1598	0.44
5	Bowman Lake	1438	0.42
6	Bucks Lake	1504	1.53
7	Butt Valley Reservoir	1589	0.31
8	Calaveras Reservoir	1719	32.75
9	Camanche Reservoir	1775	0.51
10	Camp Far West Reservoir	1555	0.00
11	Castaic Lake	1789	1.90
12	Cherry Lake	1720	0.12
13	Clear Lake	2064	22.14
14	Courtright Reservoir	1439	0.35
15	Diamond Valley Lake	1795	24.96
16	Dodge Reservoir	992	12.80
17	Don Pedro Reservoir	1881	0.27
18	Eagle Lake	2052	1.66
19	Folsom Lake	1849	3.19
20	French Meadows Reservoir	1603	0.12
21	Frenchman Lake	1524	6.89
22	Goose Lake	1477	2.64
23	Grant Lake	1644	2.19
24	Hetch Hetchy Reservoir	1686	0.30
25	Indian Tom Lake	1550	1.10
26	Indian Valley Reservoir	1853	5.50
27	Isabella Lake	2040	17.16
28	Jackson Meadows Reservoir	1337	0.07
29	Lake Almanor	1904	0.95
30	Lake Berryessa	1972	0.15
31	Lake Crowley	1803	29.73
32	Lake Davis	1602	7.62
33	Lake Earl	1331	0.98
34	Lake Eleanor	1672	0.42
35	Lake Elsinore	1982	99.34
36	Lake Hennessey	1540	6.62
37	Lake Henshaw	1841	43.40
38	Lake Mathews	1772	0.00
39	Lake Nacimiento	1804	0.22
40	Lake Oroville	1790	1.06

41	Lake Pillsbury	1809	13.16
42	Lake San Antonio	1809	17.08
43	Lake Shastina	1750	11.83
44	Lake Success	1589	0.63
45	Lake Thomas A Edison	1496	0.00
46	Little Grass Valley Reservoir	1538	0.26
47	Loon Lake	1398	0.21
48	Lower Roberts Reservoir	1700	0.71
49	Medicine Lake	966	6.73
50	Merle Collins Reservoir	1501	0.13
51	Millerton Lake	1789	4.86
52	Moon Lake	1623	1.48
53	Mountain Meadows Reservoir	1781	5.50
54	New Bullards Bar Reservoir	1699	0.06
55	Pardee Reservoir	1617	0.19
56	Perris Reservoir	1833	9.06
57	Pine Flat Lake	1794	5.07
58	Pyramid Lake	1862	18.05
59	Renner Lake	1245	5.46
60	Russian River Reservoir	1717	1.11
61	San Luis Reservoir	1979	26.02
62	Scotts Flat Reservoir	1466	0.82
63	Shasta Lake	1821	0.16
64	Shaver Lake	1764	0.00
65	Silva Flat Reservoir	926	4.21
66	Skinner Reservoir	1685	3.92
67	Sweetwater Reservoir	1663	25.32
68	Thermalito Afterbay	1796	1.00
69	Tinemaha Reservoir	1955	3.94
70	Trinity Lake	1800	0.22
71	Tule Lake	1353	17.00
72	Turlock Lake	1769	0.17
73	Union Valley Reservoir	1679	0.00
74	West Valley Reservoir	1666	5.58
75	Whiskeytown Lake	1691	0.59
76	Woodward Reservoir	1747	0.00

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Chapter 4: Remote Sensing of Cyanobacteria in California Lakes and Reservoirs: Impacts and Implications of Wildfire

Abstract:
Wildfires, increasingly prevalent in the Western US due to climate change, can significantly impact water quality by altering landscape and soil properties. Potential changes include increased nutrient transport and the promotion of harmful algal blooms (HABs). This study examines the effect of wildfires on cyanobacteria harmful algal blooms (cyanoHABs) in 68 California lakes using satellite remote sensing (SRS) data from 2008 to 2022. Findings show that most lakes had no significant difference post-wildfire, however the few that did mainly showed an increase of cyanoHABs, particularly within two years post-wildfire. Statistical analyses reveal significant trends in cyanoHAB alerts over the study period, emphasizing the need for integrated water management strategies in wildfire-prone areas. This research highlights the crucial role of remote sensing in monitoring and mitigating the ecological impacts of wildfires on water quality.

4.1 Introduction

A major portion of Western water supply comes from areas where wildfires are a frequent and growing concern (Smith et al., 2009), potentially impacting the quality of water for many people. Wildfires are increasing in both intensity and frequency due to climate change which have resulted in a significant rise in the number of large wildfires and the total area burned each year (Westerling et al., 2006; Abatzoglou & Williams, 2016; Dennison et al., 2014). Wildfire can influence post-fire runoff by altering the landscape and soil properties by burning vegetation and organic matter, leaving soil exposed and more susceptible to erosion (Neary et al., 2005; Bladon et al., 2014). Higher than usual sediment transport post-wildfire can increase nutrients in the system such as phosphorus and nitrogen (Spencer et al., 2003; Sheridan et al., 2007; Emelko et al., 2011; Mast and Clow, 2008) which can support growth of harmful algal blooms (HABs) (Fogg, 1969; Padisák, 1997; Flores and Herrero, 2005; Paerl et al., 2011).

HABs are often caused by the rapid growth of cyanobacteria, also known as blue-green algae, which can produce toxins detrimental to human and animal health. These cyanobacteria harmful algal blooms (cyanoHABs) can degrade water quality, limit recreational use of water bodies, and result in significant ecological and economic impacts (Smayda, 1997; Paerl, 2009; Stroming et al., 2020). As cyanoHABs continue to impact water quality, ecosystem health, and human well-being, addressing this issue has become a pressing national (Bladon et al., 2014; Coffer et al., 2021; Schaeffer et al., 2024) and global concern (Chorus and Bartram, 1999; Stewart et al., 2006; Chorus and Welker, 2021; Paerl and Huisman, 2009; Brooks et al., 2016).

Studies that have measured algal biomass post-fire have seen increases, decreases, or no changes at all (Robinson, 1994; Rushforth and Minshall, 1994; Klose et al., 2015; McCullough et al., 2019; Paul et al., 2022). In Tang et al. (2021) they demonstrated that the 2019 and 2020 Australian wildfires had a profound impact on marine ecosystems by triggering widespread algal blooms. A lake turbidity and chlorophyll-a, an indicator of blooms, found no clear signal globally but clearer responses were found for individual lakes (Caroni et al., 2024). This is likely because of multiple factors at play such as the timing and severity of wildfire and subsequent precipitation, and general factors that influence algal growth in the systems (Verkaik et al., 2013). Furthermore, findings are from studies focused primarily on one lake or on a few clustered lakes (McCullough et al., 2019; Urquhart et al., 2017). Even fewer studies include pre- and post-fire data, limiting our understanding of ecosystem recovery.

In recent years, remote sensing has opened new frontiers for environmental monitoring. Satellite remote sensing (SRS), with its ability to collect data over large spatial scales, provides invaluable insights into water quality dynamics. By analyzing satellite data collected over decades, we can identify long-term trends in cyanobacteria abundance, distribution, and potential exposure to toxins (Urquhart et al. 2017; Coffer et al. 2021; Schaeffer et al., 2022; Wynne et al. 2010). Water quality records are incomplete in various lakes across the United States because of inconsistent monitoring (Schaeffer et al., 2018). Using SRS, it may be possible to assess wildfire influence on cyanobacteria by examining spatial and temporal overlaps, revealing the relationship between wildfire events and algal bloom dynamics.

Our objective is to determine the relationship wildfire has on cyanoHABs in lakes across California, the largest state in the Western US and the third largest state in the US, by using available satellite remote sensing (SRS) imagery. Our hypothesis is that lakes and reservoirs whose watershed experienced a moderate or high fire severity within their watershed will experience more frequent cyanoHABs than pre-fire conditions. However, these levels may decrease after a year as vegetation cover recovers and the fire's effects on soil and hillslope hydrological properties return to pre-wildfire conditions (Smith et al., 2011; Reneau et al., 2007). We expect cyanobacteria conditions to peak within two years post-wildfire to account for ecosystem recovery (Raoelison et al., 2023; Rust et al., 2018; Nolan et al., 2014; Spencer and Hauer, 1991; Verkaik et al., 2013).

4.2 Methods

4.2.1 Study Area

Areas with Mediterranean climates, such as California, are at high risk of increased soil erosion post-wildfire because the fire season is immediately followed by the wet season (Mayor et al., 2007). The already limited water supply in California must be preserved and be monitored for safe consumption and use for the future. Focusing on California with its great climate range and variety of ecosystems (Bedford et al., 2018), would allow a new insight on wildfire’s role on water quality that could be applicable to similar ecoregions around the world where wildfire and water scarcity risk is high.

California's climate is diverse because of its varied topography and extensive latitudinal range. Coastal areas experience mild, wet winters and warm, dry summers characteristic of a Mediterranean climate (Ackerly et al., 2018; Houlton and Lund, 2018). The Central Valley, an agricultural hub, has a similar pattern but with more pronounced temperature extremes (Fernandez-Bou et al., 2022). In contrast, the Sierra Nevada mountains experience alpine conditions with cold, snowy winters and mild summers, while southeastern regions like Death Valley endure scorching desert climates, featuring some of the hottest temperatures on Earth (Hopkins, 2018; Hall et al., 2018; Kalandsky, et al., 2018).

There are a total of 68 California lakes and reservoirs that were used in our study that are resolvable through the primary satellite sensors used to measure cyanobacteria, the Medium Resolution Imaging Spectrometer (MERIS) and the Ocean and Land Color Instrument (OLCI) (Urquhart and Schaeffer, 2020). Three of the resolvable lakes were removed from our analysis. Lake Tahoe was omitted due to its extremely clear, dark waters (Wang et al., 2020) particularly in the nearshore (Pearson and Huntington, 2019) that may interfere with SRS signals. The Salton Sea and Mono Lake were removed because of its well documented and complicated hydrology and water history (Stine, 1991; Wiens et al., 1993; Holdren and Montaño, 2002; Cohen, 2009).

4.2.2 Datasets

4.2.2.1 Cyanobacteria SRS Data

SRS observations of cyanobacteria were downloaded from the Cyanobacteria Assessment Network (CyAN) (Schaeffer et al., 2015). Their products are in CI_{cyano} (CyAN, Schaeffer et al., 2015 based on Wynne et al. (2008) and modified by Lunetta et al. (2015). The satellites used to create the CI_{cyano} data are from the European Space Agency's MERIS sensor onboard the Envisat satellite, and OLCI onboard Sentinel 3. The final level-3 SRS-cyanobacteria products have clouds masked and sunglint, shadows and potential mixed pixels from water and land removed (Urquhart and Schaeffer, 2020; Schaeffer et al., 2022).

The CI_{cyano} products are available in daily and 7-day maximum value composites. Because of the large spatial coverage and lengthy time series, the weekly products were used for this study. The time period in our study for MERIS observations is 2008 to 2012 and OLCI is 2016 to 2022. We used the lake shapefiles created for the MERIS/OLCI sensors that are intended for CyAN data (Urquhart and Schaeffer, 2020), to use as the boundaries for each lake.

4.2.2.2 Wildfire Data

We used wildfire perimeter data provided by the Monitoring Trends and Burn Severity (MTBS), a comprehensive dataset created through a joint program by the U.S. Geological Survey (USGS) and the U.S. Forest Service. MTBS integrates satellite imagery from the Landsat satellites and ground-based observations for their products (MTBS, 2023). MTBS has their own severity products, but they have limitations including potential errors due to subjective severity classification thresholds that are not field-validated (Kolden et al., 2015). The wildfire severity data we used comes from Xu et al. (2022), which is based on the normalized burn ratio and the differenced normalized burn ratio from the MTBS dataset, where severity is consistently based on field-validated equations. Their dataset ranges from unburned, low, moderate, high, to grass burn. We then summarized wildfire data by calculating the proportion of the watershed burned by moderate or high severity fire and distance from the lake edge from 2008 to 2020. Our study summarized wildfire data by each lake’s corresponding watershed. We used the sub-basin level (HUC-8) as our watershed scale. Some encompass multiple watersheds, so each were given a unique identifier so the wildfire history of each could still be considered.

Higher burn severity and a larger proportion of a watershed burned significantly increase the likelihood of water quality being compromised. (Uzun et al., 2020; Hallema et al., 2018). To address smaller fires, we included only those wildfires that burned at moderate or high severity, resulting in a yearly total of 1% or more of the watershed burned. This ensured inclusion in our analysis if the combined burned area met this threshold. Using the sub-basin level to screen for wildfires, we found many fires extended over 150 km from the lake edge which may make it become more difficult to distinguish wildfire signals with such a great distance (Paul et al., 2022; Smith et al., 2011). We filtered watersheds that had at least 1% burned by moderate or high severity fires that year to have at least one wildfire within 50 km, categorizing anything beyond as “unburned.” This method retained approximately 75% of the wildfires in the dataset.

4.2.3 Cyanobacteria Time Series

We calculated the median CI_{cyano} (Equation 1) from the CyAN dataset for each lake’s weekly composite image and converted it to cyanobacteria abundance (Equation 2) (Wynne et al., 2010; Lunetta et al., 2015).

$$CI_{cyano} = 10^{\,(\text{Digital Number} * 0.011714 - 4.1870866)} \quad (1)$$

$$\text{Cyanobacteria Abundance cells/mL} = CI_{cyano} * 1E + 08 \quad (2)$$

*CyAN's range is limited from ~10,000 to 7,000,000 cells/mL

Median cyanobacteria abundance for an entire lake was calculated, and this value was used to classify the lake into public health alerts following 1999 World Health Organization guidelines following Lopez Barreto et al. (2024) (See Chapter 2 for more details). Cyanobacteria abundance that was greater than 20,000 cells/mL were classified as an alert and those below were considered as no alert. The duration and frequency of these WHO99 GVs before and after a wildfire were subsequently calculated.

CyanoHAB alert frequency was calculated as the fraction of occurrences of alerts normalized by the total number of observations (Equation 3). This was calculated separately for each lake and for each sensor time period; frequencies were calculated for 2008 to 2011 and 2016 to 2022 separately. There are about three months of MERIS data in 2012, however this is during the winter and early spring months that are outside of algal bloom season and were thus omitted. There are OLCI data beginning from early spring in 2016, before the bloom season, which were kept.

$$\text{CyanoHAB Alert Frequency (\%)} = \frac{\text{Total n of weekly lake medians above the WHO99GV}}{\text{Total n of weekly lake data}} * 100 \quad (3)$$

4.2.4 Post-wildfire Water Quality Assessment

4.2.4.1 Defining Pre- and Post-Wildfire Conditions and Time Periods

To compare the frequency of cyanobacteria alerts between pre- and post-wildfire occurrences, we defined the pre-wildfire time period to be a year’s worth of prior wildfire data to encompass seasonal variability, but not too much climatological variability. We considered two different time periods for post-wildfire: one-year, to capture the immediate effects of first flush and high precipitation events in the first wet season following a wildfire, and two years to capture lagging effects. For lakes with multiple wildfires in their watershed, we only included data where there was a minimum three-year gap between wildfire years. This gap was necessary to ensure that any altered bloom conditions from previous fires, as suggested in our hypothesis, had time to dissipate. If the gap was shorter than three years, the residual effects of the prior wildfire could still influence cyanobacteria blooms, potentially confounding our analysis. We also made sure that there was at least a full year (52 weeks) to compare pre- and post-fire conditions to ensure at least one bloom season is captured. An example is if there was a wildfire in 2011, depending how late the wildfire is, there might not be enough data to capture algal bloom seasonality.

4.2.6 Statistical Analyses

4.2.6.1 Determining Cyanobacteria and Wildfire Trends

We tested for monotonic trends for cyanoHAB alert frequency using the seasonal Kendall test for each lake (Kendall, 1938; Mann, 1945). This non-parametric test evaluates the consistency of trends, providing a robust measure of changes to identify whether cyanobacteria presence are increasing, decreasing, or remaining stable over our time period. Our analysis defined seasons as individual months as used in other cyanoHAB studies (Urquhart et al., 2017; Schaeffer et al., 2022). We used the 2008 to 2012 and 2016 to 2022 as one timeseries. We used the seasonal Kendall Tau test from the EnvStats package (version 2.8.1) in R statistical software (version 4.3.2), recommended by the EPA for studying long-term water quality
trends

4.2.6.2 Comparing CyanoHABs in Burned and Unburned Watersheds

To quantify if there is a significant difference in the distribution of cyanobacteria cell count and cyanoHAB frequency, we performed a Mann-Whitney/Wilcoxon rank sum two-sided test (Wilcoxon, 1945; Mann and Whitney, 1947) between lakes with watersheds categorized as “burned” and “unburned” for the whole time period, and for the two sensor time periods separately: 2008 to 2012 and 2016 to 2022. This was implemented using the Stats package (version 4.3.2).

4.2.6.3 Comparing Cyanobacteria Frequency Before and After Wildfire

We performed the non-parametric Mann-Whitney/Wilcoxon rank-sum two-sided test to compare distributions of bloom frequency for each lake pre- and post-wildfire. Wildfires in 2008 and from 2012 to 2016 are considered in our study but are not eligible for analysis due to lack of cyanobacteria data before 2008 and lack of data from mid-2012 until mid-2016.

4.3 Results

4.3.1 Cyanobacteria Alerts and Wildfire Trends

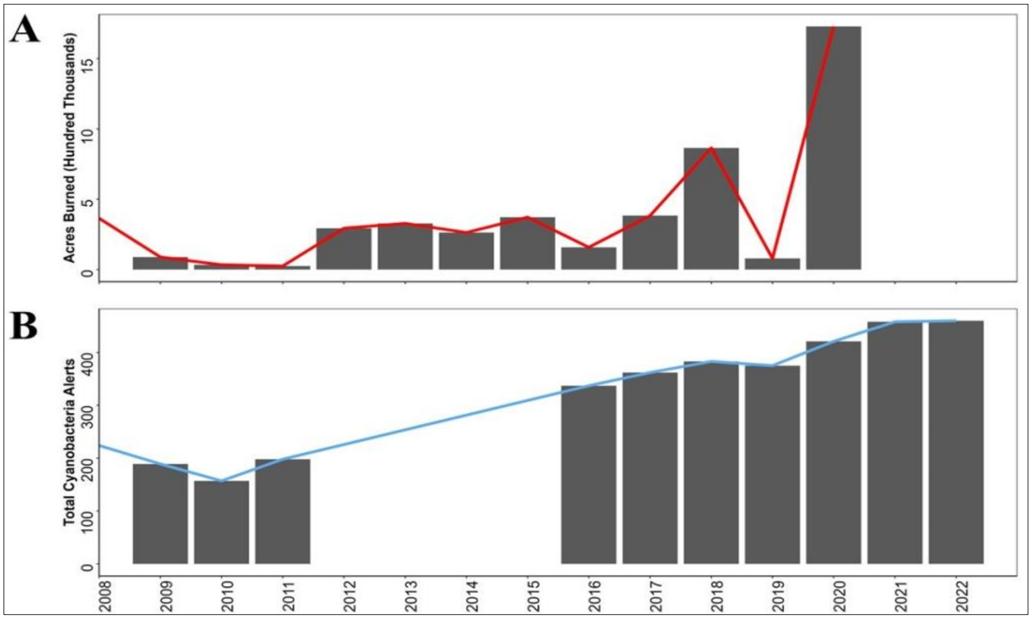

Figure 4-1. Trends in moderate and high severity wildfires and cyanobacteria alerts classified by the WHO99 GV in California from 2008 to 2022.

Areas burned by moderate and high-severity wildfires in California have been gradually increasing alongside cyanobacteria alerts from 2008 to 2020 (Figure 1). The burned area remained relatively low and stable from 2008 to around 2015, with a noticeable increase starting around 2016 (Figure 1A). A significant spike in acres burned occurred in 2018, reaching a substantial peak in 2020. There were minimal areas burned in 2019, which was an above average wet year and had very few wildfires. The number of cyanobacteria alerts from 2008 to 2011 was relatively stable according to SRS data (Figure 1B). After a data gap from 2012 to 2016, there is a general increasing trend in alerts. From 2016 onward, the alerts stabilize at a higher level compared to earlier years.

4.3.2 Statewide Cyanobacterial Trends and Alert Distribution

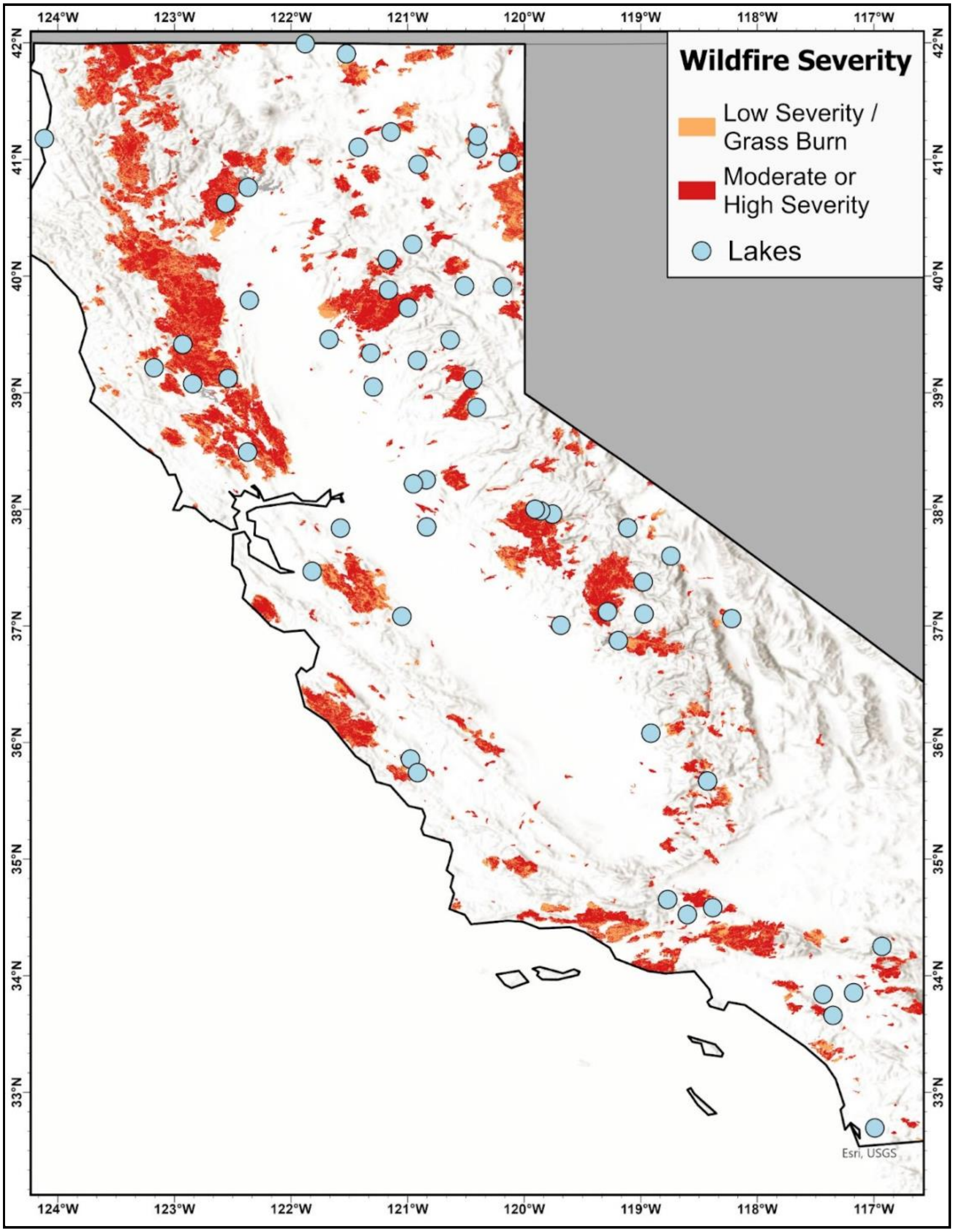

Figure 4-2. Map of California showing the spatial distribution of lakes that are SRS resolvable and used in our study. Areas affected by wildfires are displayed in orange (low severity/grass burn) and red (moderate or high severity).

Areas of moderate and severe wildfires are concentrated mainly in the northern and central parts of the state, with notable patches along the Sierra Nevada and coastal mountain ranges. Almost all lakes are in close proximity (< 5 km) of wildfires of both lower and higher severities.

Across our time series 22 lakes experienced a statistically significant trend in cyanoHAB alerts. Twenty one of the 22 lakes had an increasing trend, and only one lake, Camanche Reservoir, had a decreasing trend. While they were statistically significant, the trends for all lakes were minor and produced a Theil-Sen slope of 0, deeming them to be very minor. There is no clear spatial trend for lakes that show significant or insignificant changes. The results of our seasonal Kendall's test including the 95% confidence interval for slope, Theil-Sen slope and Kendall's tau can be found in our supplemental Table 4A-1.

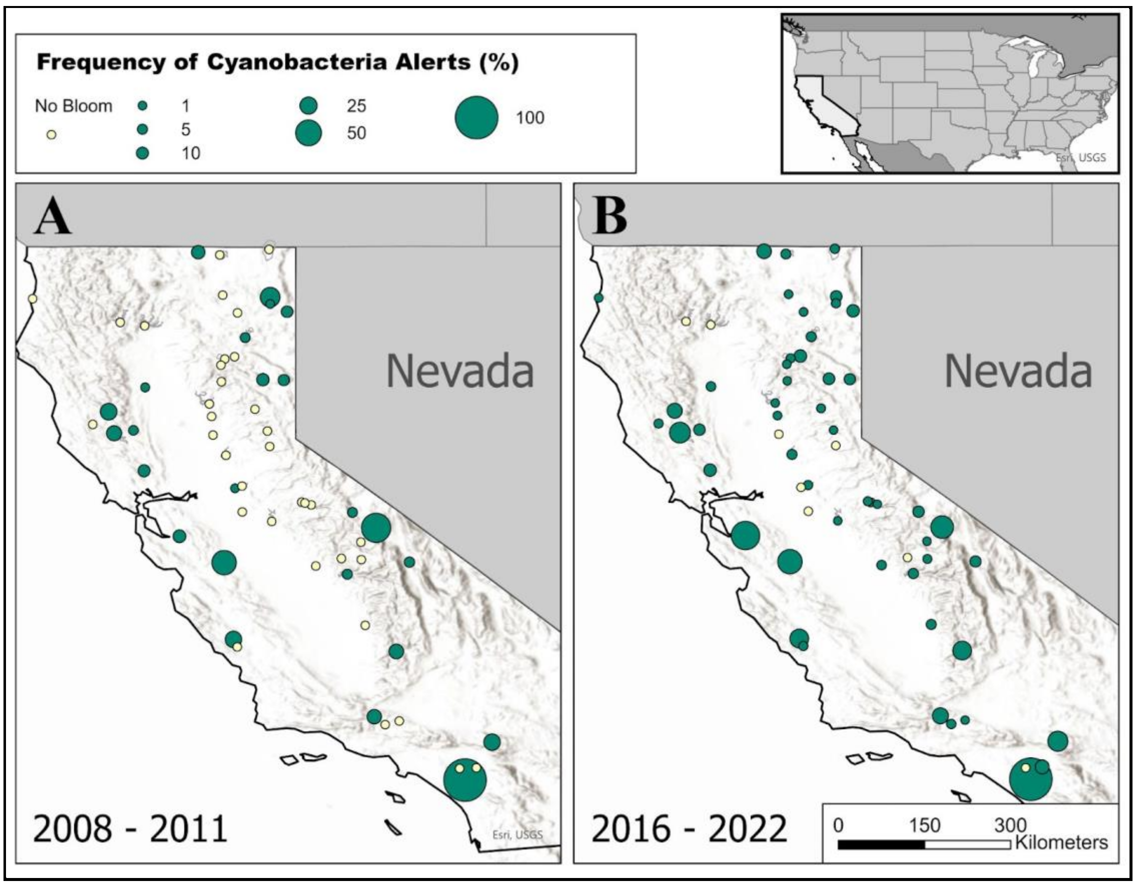

Figure 4-3. The frequency of cyanobacteria alerts for two periods: 2008-2011 on the left (A) and 2016-2022 on the right (B). The size of the circles on the maps represents the percentage of time cyanobacteria alerts were issued.

The frequency of cyanobacteria alerts in California's lakes has exhibited variability between 2008 to 2011 and 2016 to 2022 (Figure 3). Initially, from 2008 to 2011, alerts were generally less frequent, with 35 lakes showing no cyanobacteria levels above the WHO99 GV. By 2016 to 2022, however, there is a noticeable increase in both the number and size of alerts, indicating more frequent and widespread cyanobacteria blooms across the state.

The distribution of cyanobacteria alerts reveals different patterns for 2008 to 2011 versus 2016 to 2023 (Figure 4). In the earlier time period, lakes with cyanobacteria alerts were primarily found in northern and central California. Lakes with blooms primarily experienced a cyanoHAB frequency less than 10% (Figure 4), meaning that these lakes generally had occasional blooms. In the later period, the spatial distribution of lakes containing blooms is greater, having now more alerts across California compared to the earlier period. During this later period, only eight lakes remained free of blooms, while one lake transitioned from having blooms in 2008 to 2011 to no blooms in 2016 to 2022.

4.3.3 Comparing Cyanobacteria Levels and Frequency in Burned and Unburned Watersheds

Table 4-1. The results of a Mann-Whitney/Wilcoxon test comparing cyanobacteria median levels and cyanobacteria alert frequencies between burned and unburned lakes across different time periods. The mean and median of the cyanobacteria cell counts for burned and unburned lakes across different time periods. The mean and median of the cyanobacteria cell counts for burned and unburned lakes are also displayed.

Time Period	**Median Unburned (n of observations)**	**Mean Unburned**	**Median Burned (n)**	**Mean Burned**	**W-statistic**	**P-Value**
Lake-wide Median Cyanobacteria Cell Counts						
Full Time Series	6310 (12759)	91167	6310 (28427)	83845	183833339	< 0.001
2008 - 2012	6310 (9708)	54804	6310 (5633)	21773	28363645	< 0.001
2016 - 2022	6310 (8038)	109524	6310 (17807)	112967	72219627	0.038
Classified WHO99GV Cyanobacteria Alerts						
Full Time Series	-		-		183390690	< 0.001
2008 - 2012	-		-		28363645	< 0.001
2016-2022	-		–		71972382	0.174

For the entire time series, the median cyanobacteria cell count was the same for lakes with burned watersheds as for those with unburned watersheds, while the mean count was lower in burned lakes, with a very low p-value indicating a significant difference between the two groups. (Table 1). This pattern held for the 2008 to 2012 period, with cell counts remaining the same for both categories, a high W-statistic, and a very low p-value. The difference in the mean is the greatest for the time period, where the unburned is twice as high. However, in the 2016 to 2022 period, while the median cell count remained unchanged, the W-statistic was lower, and the p-value indicated a slight reduction in statistical significance. The mean for burned watersheds is now higher than those that were unburned, but the difference is not as large compared to the earlier period.

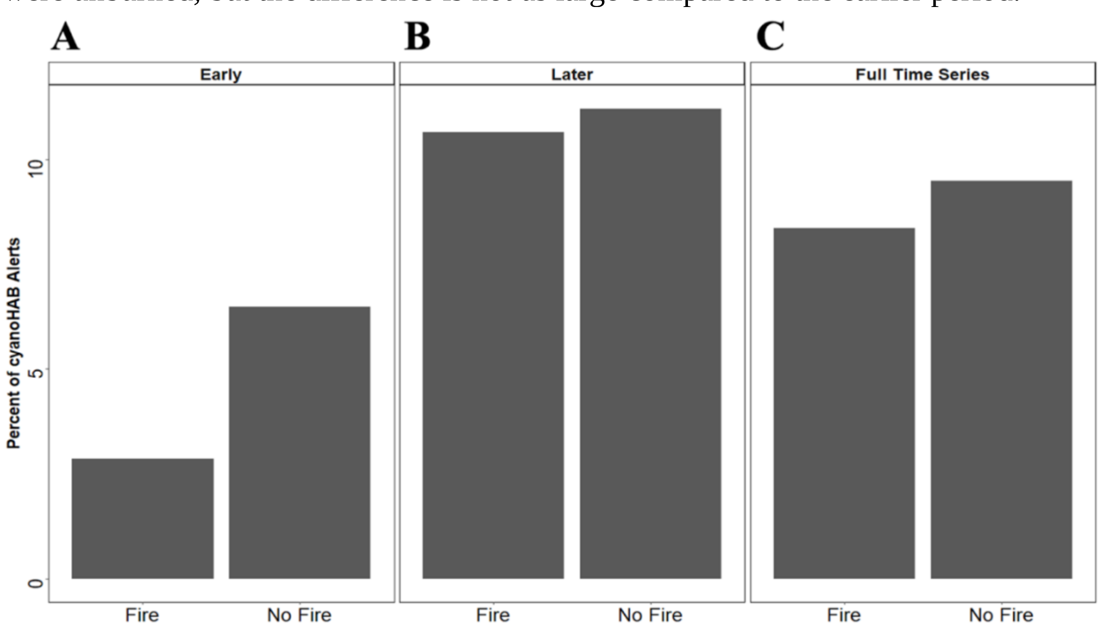

Figure 4-4. The percentage of cyanoHAB alerts across our earlier time period (2008 to 2012), later (2016 to 2022) and the entire time period for lakes with burned and unburned watersheds.

Over the full time series, lakes without wildfire had a slightly higher percentage of cyanoHAB alerts compared to those with fire (Figure 5C). In the early period, lakes without fire had a higher percentage of cyanoHAB alerts compared to lakes with fire (Figure 5A). In the later period, the percentage of cyanoHAB alerts increased significantly for both, with both categories showing almost equal percentages (Figure 5B).

4.3.4 Comparison of Cyanobacteria Presence Before and After Wildfire

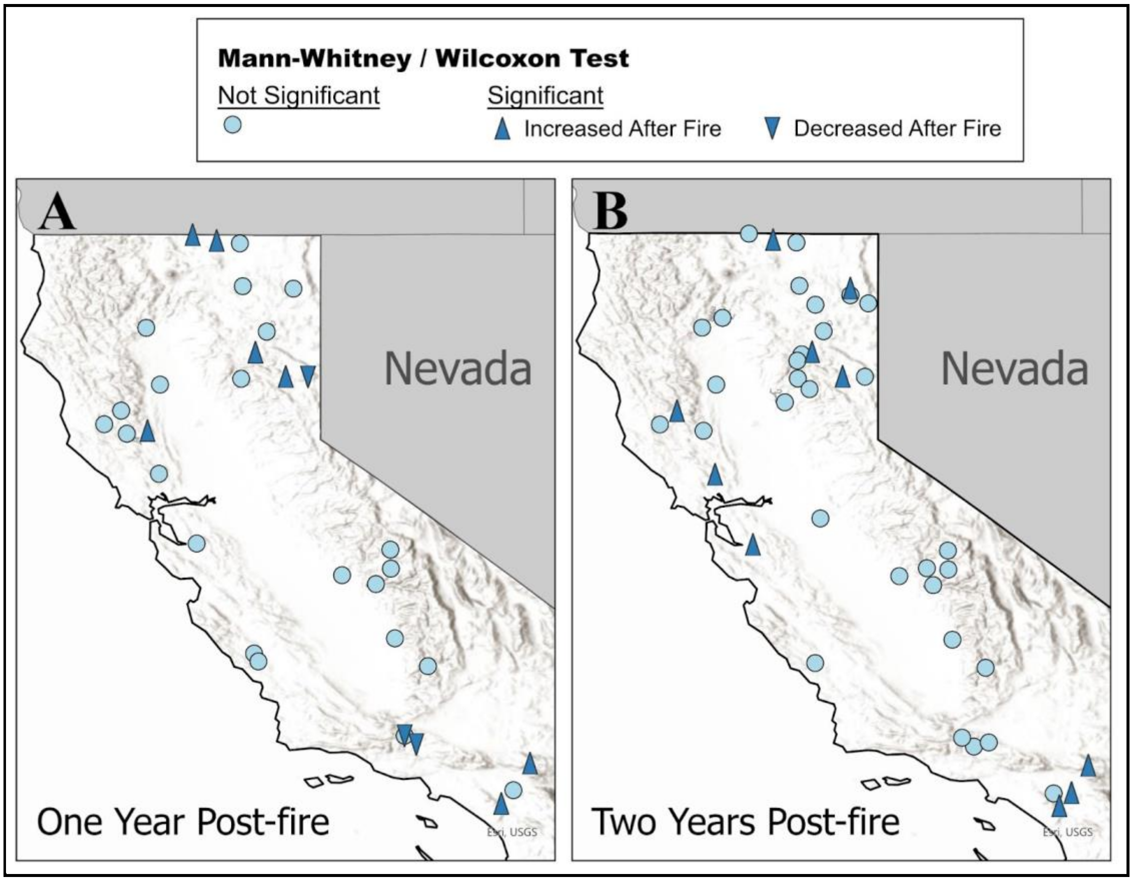

Figure 4-5. A visualization of the results of a Mann-Whitney/Wilcoxon test, with an alpha level of 0.05, comparing cyanobacteria alert frequencies before and after wildfires one year post-fire (A) and two years post-fire (B) for data from 2008 to 2012 and 2016 to 2022. Lakes that are either significant or not significant that appear in only one map indication one or two years post-fire are because of insufficient data for the time period (i.e one year needs at least 40 weeks of data, and two years requires at least 60).

The majority of lakes analyzed for differences in cyanobacteria alerts pre- and post-wildfire showed no significant difference, however there were variations between the first and second years post-fire for those that did (Figure 5). Twenty-eight lakes experienced wildfires in their watersheds from 2008 to 2012 and 2016 to 2020, fitting our criteria to compare cyanobacteria alert frequencies before and after wildfires.

In the first year post-fire, seven lakes showed a significant increase in cyanoHAB alerts, while three decreased. Two years post-fire, more lakes (compared to the first year post-wildfire) experienced significant changes: eleven lakes had significant increases in alerts, and two had decreases. Despite these changes, non-significant differences still dominate the majority of lakes. Nine lakes shifted between significant and non-significant change in cyanoHAB alerts between both periods.

4.4 Discussion

The primary objective of our study was to determine if wildfire impacts the frequency of cyanoHAB alerts in California lakes and reservoirs. The proximity of these expanding wildfires to lakes within the state (Figure 2) raises significant concern, warranting investigation into any potential relationship with algal blooms (California Coastkeeper Alliance, 2023; National Park Service, 2023). Our study found that lakes with wildfires in their watersheds have fewer cyanoHAB alerts (8.4%) than those that remain unburned (9.5%), although while statistically significant, the differences are relatively small. We also found that the most significant increases in cyanobacteria alerts occurred two years post-fire, compared to the first year. One year post-fire, significant changes in cyanobacteria alerts were primarily observed in the northern and southern regions of California. By two years post-fire, a greater number of sites exhibited significant increases in cyanoHAB alerts, with these sites now extending into the central region of the state. There are only three instances from the earlier time period, but all were deemed insignificant. The few observations are primarily from insufficient data that was needed to establish pre and post wildfire conditions, however there were also overall less wildfire during this period (Figure 1).

We found a statistically significant increasing cyanoHAB alert trend in both 2008 to 2011 and 2016 to 2022, however it was minor. Two previous studies measuring cyanoHAB spatial extent using MERIS for 2008 to 2012 (Urquhart et al., 2017) and OLCI for 2017 to 2020 (Schaeffer et al., 2022) found that California lakes overall had little direction and strength in their Mann-Kendall trend test results. Both studies found similar results, despite our use of the lakewide median and their use of spatial extent. However, the time periods examined differ, and while they conducted a statewide comparison, we focused on individual lakes. When we viewed the statewide cumulative sum of total cyanobacteria alerts using the WHO99 GV, we saw that the range of values were similar separating 2008 to 2011 and 2016 to 2022 (Figure 1B) from each other, which is what Urquhart et al. (2017) and Schaeffer et al. (2022) are also respectively finding in their trend tests. Our lakes that show a strong increase over time (Figure 2) are likely due to a gradual increase from the missing five years of data.

Overall, cyanobacteria alerts have been trending upward over the entire time series, driven by a substantial increase in alerts between the two periods studied. The differences in cyanoHAB alerts are less pronounced in the 2016 to 2022 period relative to the 2008 to 2012 period. Concurrently, wildfires have also been on the rise. The state's wildfire season has extended, with fires occurring earlier in the spring and lasting later into the fall. Some of the most destructive and largest fires in California's history, such as the Camp Fire in 2018 and the August Complex Fire in 2020, occurred during our later half of the study (Cal Fire, 2022). Historically, when wildfires were less frequent, their suppressing effects on cyanoHABs might have been more pronounced. Alternatively, cyanoHABs may have primarily occurred in lakes with low fuel loads and specific locations, such as agricultural areas, that were less likely to burn. In the later period, as fires have become more intense, cyanoHABs have worsened statewide. This suggests that more intense fires could be contributing to the increase in cyanoHABs, potentially reducing the difference between "burned" and "unburned" areas. Another explanation could be that cyanoHABs are now spreading into regions more susceptible to burning under the new fire regime.

Our findings suggest that while some lakes might recover or stabilize relatively quickly post-fire, others may endure prolonged periods of elevated cyanobacteria levels. All sites with significantly decreasing cyanoHABs (Castaic, Frenchman, and Pyramid Lakes) demonstrated a notable shift to no significant change in cyanobacteria levels by the second year post-fire, indicating possible recovery. In contrast, some sites that initially experienced increases in cyanobacteria alerts the first year shifted to insignificant by the second year (Indian Tom Lake and Indian Valley Reservoir). All sites that showed signs of recovery were reservoirs but were spatially distributed across the state. The characteristics of the wildfire and antecedent lake conditions likely influence the lake's resiliency and recovery. Productive lakes, already rich in nutrients, might not experience increased algal growth after a fire, indicating a level of resilience. In contrast, oligotrophic lakes, which are typically low in nutrients, are more likely to undergo significant changes in response to nutrient inputs from fire runoff (Paul et al., 2022; Cunillera-Montcusi et al., 2019). This variability in response highlights the importance of understanding specific lake conditions to develop effective recovery strategies and enhance resilience to disturbances.

Of the three sites that experienced a decrease, two (Castaic and Pyramid Lake) were in close proximity to each other in the Sierra Pelona Mountains in southern California (Figure 4A). This regional clustering may suggest that the impact of wildfires on cyanobacteria levels may be influenced by local environmental conditions and specific post-fire management practices. Because of the close proximity, these two lakes share near identical precipitation, temperature, and similar wildfire regimes which may explain why they both have identical results. Because of wildfires in 2020, several projects became listed as “high priority” regarding post-fire forest and watershed restoration in the Sierra Pelona Mountains. Projects included reducing invasive species in wildfire prone areas, reducing road sediment, improving water infrastructure, and maintenance of the existing chaparral and conifer plantations to help facilitate recovery (National Fish and Wildlife Foundation, 2021). The recovery from these sites may be a result from these management decisions, or perhaps some lakes might recover or stabilize relatively quickly post-fire, and others may endure prolonged periods of elevated cyanobacteria levels.

Drought and wet years significantly impact the occurrence and severity of algal blooms. During droughts, reduced water flow and increased temperatures create stagnant conditions ideal for algal growth, exacerbated by concentrated nutrients from runoff (Gámez et al., 2019; de Barroso et al., 2018; Lehman et al., 2017; García-Prieto et al., 2012). Conversely, wet years bring increased runoff and nutrient loading from rainfall and snowmelt, which can trigger blooms, although increased flow can sometimes dilute and flush out nutrients, reducing bloom severity (Michalak, 2016; Reichwaldt and Ghadouani 2012).

Over the past two decades, California has experienced notable wet years interspersed with severe droughts. Wet years such as 2005, 2010 to 2011, and 2016 to 2019 brought significant precipitation that replenished reservoirs, boosted groundwater supplies, and increased river flows (Parrett and Hunrichs, 2006). Conversely, drought years like 2007 to 2009, 2012 to 2016, and 2020 to 2022 were marked by critically low precipitation, leading to severe water shortages, depleted reservoirs, and stressed ecosystems. The 2012 to 2016 drought was particularly devastating, being one of the most prolonged and severe in California's history (Lund et al., 2018; Ullrich et al., 2018).

Castaic, Frenchman, and Pyramid lakes experienced wildfires at the onset of the 2020 to 2022 drought. The minimal precipitation during these years likely restricted the mobilization of nearby sediment and nutrients that would typically be more mobile. In contrast, Lake Elsinore, Big Bear Lake, and Indian Valley Reservoir, which saw significant increases in cyanoHAB alerts, had wildfires during the 2016 to 2019 wet period. The increased runoff from these wet years may have contributed to the heightened cyanoHAB activity. These climate extremes were not directly considered in our study, however these are likely contributing cyanoHAB factors that should be considered in the future.

Cyanobacteria blooms are influenced by multiple factors beyond wildfires, including nutrient loading, water temperature, hydrology, light availability, and climate extremes. While wildfires can contribute to algal growth through nutrient enrichment and altered water chemistry, other environmental factors are equally crucial (Emelko et al., 2016; Cook and Holland, 2012; Olson et al., 2023). Even without wildfires, significant cyanobacteria blooms can occur if these conditions are met. Therefore, these variables should be considered when interpreting study results, highlighting a limitation in large-scale studies.

4.5 Conclusions

We aimed to determine the relationship between wildfires and cyanoHABs in lakes across California as wildfires become more frequent and severe due to climate change. Overall, our findings highlight the complex interplay of factors driving changes in cyanoHAB alert frequencies in California's lakes. The observed reduction in the difference between burned and unburned lakes during 2016 to 2022, coupled with the general increase in bloom occurrences, emphasizes the need for continued research and monitoring to understand and mitigate the impacts of these environmental changes on water quality and public health. While most sites did not have a statistically significant increase in cyanobacteria alerts post-fire, those that did primarily showed increases, with some recovering by the second year. The persistence of significant changes two years post-fire emphasizes the lasting impact of wildfires on aquatic ecosystems, necessitating long-term monitoring and management strategies to mitigate adverse effects on water quality and public health. This variability underscores the complex interactions between wildfire effects and aquatic ecosystems, highlighting the necessity for region-specific studies to understand local dynamics better.

After a wildfire, management strategies that can protect water quality would be to implement erosion control measures, maintain riparian buffer zones, and manage nutrient levels to prevent algal blooms. Enhancing water treatment facilities to handle increased sediment and nutrient loads is crucial, along with conducting regular water quality monitoring to address issues promptly. Management done for Castaic and Pyramid Lake post-wildfire might be the reason why they recovered from previous cyanoHAB changes within two years. Public advisories are also important to inform the community about potential water quality risks and safe usage guidelines. These measures help mitigate wildfire impacts on water quality, safeguarding aquatic ecosystems and public health. Further studies are necessary to disentangle the specific contributions of wildfire activity, climate change, and land use changes to improve the understanding of the observed trends in cyanobacteria blooms.

4.5 Appendix

Table 4A-1. The results of the seasonal Mann-Kendall for cyanoHAB alerts across 76 lakes in California from 2008 to 2012 and 2016 to 2023.

Lake Name	Tau	Slope	Intercept	$\chi 2$	Z-Trend	Lower Interval	Upper Interval
Big Bear Lake	0.19	0	0	NA	0.00	0	0
Big Lagoon	0.02	0	0	NA	0.09	0	0
Black Butte Lake	0.03	0	0	NA	0.31	0	0
Bouquet Reservoir	0.00	0	0	NA	1.00	0	0
Bowman Lake	0.05	0	0	NA	0.06	0	0
Bucks Lake	0.00	0	0	NA	1.00	0	0
Butt Valley Reservoir	0.02	0	0	NA	0.22	0	0
Calaveras Reservoir	0.32	0.08	-294.1	0.07	0.00	0	0
Camanche Reservoir	-0.02	0	0	NA	0.16	0	0
Camp Far West Reservoir	0.00	0	0	NA	NA	0	0
Castaic Lake	0.01	0	0	NA	0.78	0	0
Cherry Lake	0.03	0	0	NA	0.08	0	0
Clear Lake Reservoir	0.09	0	0	NA	0.00	0	0
Clear Lake	0.26	0	-100.9	NA	0.00	0	0
Courtright Reservoir	0.03	0	0	NA	0.25	0	0
Diamond Valley Lake	0.21	0	0	NA	0.00	0	0
Dodge Reservoir	0.04	0	0	NA	0.26	0	0
Don Pedro Reservoir	0.00	0	0	NA	1.00	0	0
Eagle Lake	0.03	0	0	NA	0.48	0	0
Folsom Lake	0.05	0	0	NA	0.07	0	0
French Meadows Reservoir	0.01	0	0	NA	0.64	0	0
Frenchman Lake	0.00	0	0	NA	1.00	0	0

Goose Lake	0.05	0	0	NA	0.05	0	0
Grant Lake	0.08	0	0	NA	0.05	0	0
Hetch Hetchy Reservoir	0.00	0	0	NA	0.87	0	0
Howard Prairie Lake	0.12	0	0	NA	0.01	0	0
Indian Tom Lake	0.06	0	0	NA	0.01	0	0
Indian Valley Reservoir	0.06	0	0	NA	0.07	0	0
Isabella Lake	0.10	0	0	NA	0.03	0	0
Jackson Meadows Reservoir	0.02	0	0	NA	0.40	0	0
Lake Almanor	0.07	0	0	NA	0.00	0	0
Lake Berryessa	-0.01	0	0	NA	0.64	0	0
Lake Crowley	0.10	0	0	NA	0.04	0	0
Lake Davis	0.09	0	0	NA	0.02	0	0
Lake Earl	-0.12	0	0	NA	0.00	0	0
Lake Eleanor	0.04	0	0	NA	0.07	0	0
Lake Elsinore	0.30	0	4	0.70	0.00	0	0
Lake Hennessey	0.06	0	0	0.80	0.17	0	0
Lake Henshaw	0.27	0	0	0.81	0.00	0	0
Lake Mathews	0.00	0	0	NA	NA	0	0
Lake Nacimiento	0.02	0	0	NA	0.41	0	0
Lake Oroville	0.01	0	0	NA	0.27	0	0
Lake Pillsbury	0.02	0	0	NA	0.75	0	0
Lake San Antonio	0.03	0	0	NA	0.58	0	0
Lake Shastina	0.03	0	0	NA	0.53	0	0
Lake Success	0.04	0	0	NA	0.12	0	0
Lake Thomas A Edison	0.01	0	0	NA	0.56	0	0.2
Little Grass Valley Reservoir	0.03	0	0	NA	0.04	0	0
Loon Lake	0.02	0	0	NA	1.00	0	0
Lower Roberts Reservoir	0.00	0	0	NA	1.00	0	0
Medicine Lake	0.29	0	0	NA	0.00	0	0
Merle Collins Reservoir	0.01	0	0	NA	0.52	0	0
Millerton Lake	0.05	0	0	NA	0.06	0	0
Moon Lake	0.01	0	0	NA	0.52	0	0
Mountain Meadows Reservoir	0.18	0	0	NA	0.00	0	0
New Bullards Bar Reservoir	0.02	0	0	NA	0.29	0	0
Pardee Reservoir	0.05	0	0	NA	0.03	0	0
Perris Reservoir	0.21	0	0	NA	0.00	0	0
Pine Flat Lake	-0.02	0	0	NA	0.59	0	0

Pyramid Lake	0.08	0	0	NA	0.02	0	0
Renner Lake	-0.05	0	0	NA	0.24	0	0
Russian River Reservoir	0.04	0	0	NA	0.05	0	0
San Luis Reservoir	0.18	0	0	NA	0.00	0	0
Scotts Flat Reservoir	0.05	0	0	NA	0.03	0	0
Shasta Lake	0.00	0	0	NA	NA	0	0
Shaver Lake	0.00	0	0	NA	NA	0	0
Silva Flat Reservoir	0.02	0	0	NA	0.30	0	0
Skinner Reservoir	0.05	0	0	NA	0.14	0	0
Sweetwater Reservoir	0.27	0	0	NA	0.00	0	0
Tinemaha Reservoir	0.05	0	0	NA	0.15	0	0
Trinity Lake	0.00	0	0	NA	NA	0	0
Tule Lake	0.10	0	0	NA	0.03	0	0
Turlock Lake	0.00	0	0	NA	NA	0	0
Union Valley Reservoir	0.00	0	0	NA	NA	0	0
Upper Klamath Lake	0.03	0	0	NA	0.47	0	0
West Valley Reservoir	-0.12	0	0	NA	0.00	0	0
Whiskeytown Lake	0.05	0	0	NA	0.02	0	0.1
Woodward Reservoir	0.00	0	0	NA	NA	0	0

Table 4A-1: The results of the seasonal Mann-Kendall for cyanoHAB alerts across 76 lakes in California from 2008 to 2012 and 2016 to 2023.

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Chapter 5: Conclusions

Satellite remote sensing (SRS) is important for monitoring water quality, due to its ability to provide comprehensive, timely, and cost-effective data over large spatial scales. This technology fills significant temporal and spatial gaps left by traditional in-situ methods, enhancing the ability to manage and mitigate the impacts of cyanobacterial harmful algal blooms (cyanoHABs) on water resources and public health. The integration of SRS with existing monitoring frameworks offers a powerful tool to address the growing challenges posed by climate change on aquatic ecosystems.

This dissertation highlights the effectiveness of SRS in monitoring cyanoHABs and supporting public health advisories across California's diverse lake environments. By integrating SRS with in-situ monitoring, the studies reveal significant regional variations in cyanoHAB frequency and emphasize the critical role of environmental factors such as climate, urbanization, and agricultural runoff. The findings also underscore the persistent impact of wildfires on aquatic ecosystems, demonstrating the need for sustained, adaptive management strategies to protect water quality and public health in the face of changing environmental conditions.

Chapter 1 proves the effectiveness of using satellite remote sensing (SRS) to monitor cyanoHABs and for recreational health advisories in California. The research leverages chlorophyll-a (chl-a) as a proxy for cyanobacteria, aligning with updated WHO guidance values. Using Sentinel-2 (S2) and Sentinel-3 (S3) satellites, the study creates SRS-derived chl-a and cyanobacteria and compares these findings with advisories issued by the California Department of Water Resources. The results show a high total agreement rate for S3 and variable rates for S2 depending on the algorithm, indicating that SRS can effectively complement traditional monitoring methods. The study underscores the potential of SRS to fill temporal and spatial data gaps, thereby enhancing public health protection through more comprehensive and timely monitoring of water quality in cyanobacteria-dominated lakes and reservoirs.

Chapter 2 underscores the critical importance of combining satellite remote sensing (SRS) data with in-situ monitoring to effectively assess and manage cyanobacteria cyanoHABs across lakes in California. The increased spatial coverage provided by SRS ensures a more accurate representation of cyanobacteria distribution, enhancing overall monitoring and assessment of cyanoHABs. However, integrating in-situ data with SRS is crucial for better understanding toxicity rates. The spatial and temporal inconsistencies in cyanotoxin presence underscore the need for targeted, high-resolution monitoring strategies. The study also highlights the higher accuracy of point-based cyanotoxin monitoring over lake-wide summaries in detecting localized algal blooms and associated risks. Among the five study lakes, San Luis and Perris Reservoir had the highest cyanotoxin rates, with reasonable agreement (~70%) between point-based and lake-wide approaches. Lake Oroville and Castaic Lake had the lowest cyanotoxin alerts and the highest overall accuracy (OA), indicating SRS is more effective at lower cyanobacteria levels. Balanced accuracy (BA) versus OA shows that lake-wide approaches can underestimate variability and hotspots within a lake. The spatial and temporal inconsistencies in cyanotoxin presence underscore the need for targeted, high-resolution monitoring strategies. In high-risk regions like Southern California, combining remote sensing data with traditional sampling can enhance monitoring precision and resource allocation. Identifying lakes with persistent high advisory levels allows for prioritizing these areas for intensive study and intervention. Combining satellite remote sensing (SRS) with in-situ data collection provides a robust framework for understanding cyanobacteria dynamics and mitigating their impacts.

Chapter 3 has established a nuanced understanding of the relationship between wildfires and cyanoHABs in California lakes using SRS data from 2008 to 2022. The study found that while the majority of lakes showed no significant difference in cyanoHAB frequencies post-wildfire, those that did exhibit changes primarily demonstrated an increase in cyanoHAB activity, particularly within two years following a wildfire. This pattern suggests a persistent influence of wildfires on aquatic ecosystems, underscoring the need for sustained monitoring and management to mitigate adverse effects on water quality and public health. The observed variability in cyanoHAB responses among different lakes highlights the complexity of interactions between wildfire impacts and aquatic environments. Factors such as pre-existing nutrient levels, lake productivity, and specific local conditions significantly influence a lake's resilience and recovery post-wildfire and should be considered for each site. Additionally, regional management practices, such as those implemented in Castaic and Pyramid Lakes, may have proven effective in mitigating post-wildfire impacts, suggesting that targeted interventions can enhance lake recovery.

Given the increasing frequency and severity of wildfires due to climate change, this dissertation emphasizes the importance of integrated water management strategies. These strategies should include erosion control measures, maintenance of riparian buffer zones, and enhancements to water treatment facilities to handle increased sediment and nutrient loads. Regular water quality monitoring and public advisories are crucial to promptly address issues and inform communities about potential risks. Overall, this research underscores the critical role of SRS in advancing our understanding of environmental changes and their impacts on water quality. Continued research and adaptive management practices are essential to safeguard aquatic ecosystems and public health in the face of escalating wildfire activity.