Computational methods and autonomous robotics systems for modeling and predicting harmful cyanobacterial blooms (Extended Abstract)

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Abstract— **This extended abstract describes a joint effort to model and predict harmful cyanobacterial blooms in lakes of an interdisciplinary team with expertise in big data, environmental science, ecology, human demography, instrumentation, and robotics from four states: Maine, New Hampshire, Rhode Island, and South Carolina. This project uniquely integrates current methodology for data collection, including remote sensing and manual limnological sampling, together with heterogeneous robotic and sensor systems to extend the spatial and temporal sampling. Such big amount of data will be analyzed and processed using ensemble prediction models for determining the development and severity of blooms both in time and space (when and where) and for testing limnological hypotheses. While this project just started and does not have new result yet, this paper provides insights on open research questions and the methodology used, as well as best practices for interdisciplinary collaboration across different departments, institutions, and citizen scientists.**

I. INTRODUCTION

This project will address harmful cyanobacterial blooms (HCBs) with data collected by Unmanned Aerial Vehicles (UAVs), Autonomous Surface Vehicles (ASVs), deepwater buoys, manual sampling from boats and docks, and weather stations. The resulting 'big data' will be processed on-board and in a data center, with the goal of having the UAVs, ASVs, and buoys cooperate with one another to facilitate adaptive sampling strategies (Fig. 1).

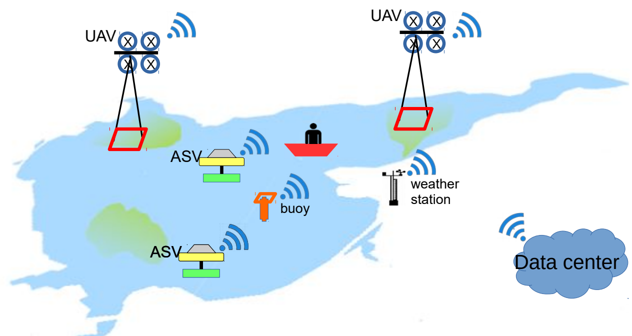

Fig. 1: Illustration of the envisioned system for monitoring and predicting harmful blooms.

Freshwater lakes are a crucial and primary source of water for human use, including drinking, irrigation, cooling, recreation, food production, and dilution of wastes and pollutants [1]. However, the provisioning of these essential services is threatened by the increased incidence of harmful cyanobacterial blooms (HCBs) in lakes worldwide [2], [3]. HCBs decrease water quality, clarity, and aesthetics (e.g., [4], [5]); negatively impact property values [6], [7], [8]; and can threaten human and animal health through the production of potent toxins that damage organ systems [9], [10]. Understanding the development of these blooms is therefore a crucial research need as well as a practical question for water quality managers and municipal water suppliers.

Limnologists have a relatively poor understanding of where blooms originate, how they develop over time, how they spread across the lake (especially relative to 'sensitive' areas like public beaches and drinking water intake pipes), and the local factors that modulate these processes across different types of lakes (for example as a function of climate, trophic state, morphometry, and depth).

Progress in answering these questions has likely been stifled by (1) limited spatial and temporal resolution of data collection, and (2) lack of analytical and modeling tools to integrate and utilize, in real-time or near-real time, the data for adaptive sampling of and forecasting blooms. Currently, researchers rely on three primary types of data about lakes: (1) manual sampling of physical, chemical, and biological metrics by researchers or trained volunteers at selected sites within each lake at weekly to monthly intervals during the potential bloom season [11], [12]; (2) high-frequency monitoring buoys located at a single, central site with sensors that measure selected physical and chemical parameters at sub-hourly to hourly intervals during the ice-free season [13]; and (3) remotely sensed data at spatial and temporal scales determined by satellite sensors, flyover timing, and weather conditions (e.g., [14], [15], [16], [17]). Unraveling the drivers of where, when, and how cyanobacterial blooms develop and spread is limited by the lack of integration of these data and limited capability for adaptive sampling.

To fill these gaps and achieve the overarching goal, the team will use machine learning techniques and robotic technologies to (1) generate high-resolution spatial and temporal data collected with UAVs and ASVs that embed intelligent adaptive sampling, (2) integrate these data streams in near-real-time, and (3) use machine learning approaches to improve sampling and prediction capabilities of models for

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bloom development. The proposed new systems, methods, and models will be extensively evaluated through comparisons with existing data and ongoing field sampling across a broad gradient of 'testbed' lakes that leverage partnerships between participating institutions and local lake associations, municipal water providers, and state agencies.

II. APPROACH AND METHODOLOGY

The project falls into three phases over the course of four years: (1) Design and Data Acquisition, (2) Synthesis and Modeling, and (3) Translation. Within each of these phases, activities develop physical hardware, software, and data sets that will advance the science of information technology, robotics, and limnology and consider how the results might be utilized by lake managers.

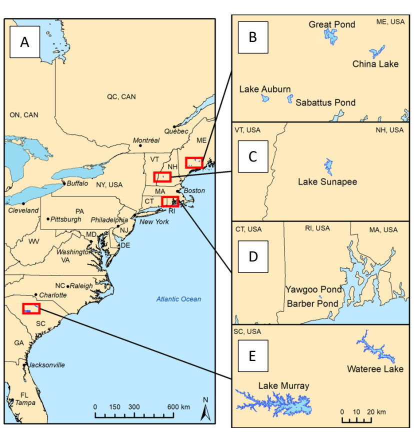
A. Phase 1: Design and Data Acquisition

The data collection effort will cover a suite of lakes that differ in many key characteristics, including latitude, size, trophic state, maximum depth, water residence time, and watershed area and land use (Fig. 2) but that have histories of blooms. Two main data collection approaches will be used. First, traditional methods for limnological sampling, i.e., manual sampling and buoys, as well as remote sensing and demographic information.

Second, we propose to combine ASVs with UAVs for real-time multi-modal sensing of cyanobacterial blooms. Coordination between the ASVs and UAVs will coordinate based on the current identification of cyanobacterial blooms and estimation of their spatial distribution. UAVs will be equipped with hyperspectral and multispectral cameras. The ASVs will be custom-made and equipped with a water quality sonde with probes measuring temperature, conductivity, DO, pH, phycocyanin/chlorophyll, and nitrate.

In literature, the problem of sampling with robots is called *informative path planning*. One solution is to focus on a single robot [18], [19], [20], [21], [22], [23], [24], [25], [26], [27], [28] or coordinate multiple robots [29], [30] in a centralized way. Others have proposed coordination methods that are implicit as embedded within the objective function that evaluates candidate locations [31], [32], [33] or explicit negotiation with other robots [34], [35], [36], [37]. Typically, the robots are assumed to be the same type and able to broadcast information without communication constraints.

Research questions will revolve around how to achieve effective coordination between these heterogeneous cyber-physical systems under communication constraints, together with humans, so that the usual limnological sampling can be improved. We plan for an experimental campaign that spans over the US East Coast (Fig. 2).



F Lake characteristics, from north to south

Lake or Pond	Trophic state*	Max. depth (m)	WS⁺ Area (km²)
Great	M	21	82.8
China	E	26	69.1
Auburn	M	36	41.2
Sabbatus	E	5	74
Sunapee	O	34	104
Yawgoo	M	11	4.3
Barber	ME	4	1
Wateree	E	24	1542
Murray	E	61	2260

* O = oligotrophic, M = mesotrophic, E = eutrophic, ME = mesoeutrophic

⁺ WS = watershed

Fig. 2: Map of the study area (A), with boxes for each region (B-E) showing the lakes at the same scale and information about trophic state, maximum depth, and watershed area (F).

TABLE I: Selected a priori hypotheses (H), with rationale (R), regarding bloom initiation, proliferation, and spread, as drawn from the limnological literature.

H1. **Blooms start in shallow, downwind coves with high human population densities and/or stream inflows in morphometrically complex lakes.** R1.1. Shallow coves have warmer temperatures, facilitating germination and recruitment (Carey et al. 2014). R1.2. Benthic resting stages accumulate in downwind areas (Carey et al. 2014). R1.3. Areas with more people have more nutrients, especially in rural areas with aging septic systems. R1.4. Stream inflows are where watershed nutrients enter the lake (Wetzel 2001).
H2. Blooms occur more often and proliferate faster in warmer water temperatures. R2.1. Cyanobacteria tend to outcompete eukaryotic phytoplankton at warmer temperatures (e.g., Wetzel 2001, Reynolds 2006, Paerl and Huisman 2008).
H3. Blooms occur more often and proliferate faster in more strongly stratified conditions. R3.1. Cyanobacteria outcompete eukaryotic phytoplankton in strongly stratified water columns (e.g., Reynolds 2006, Sommer et al. 2012).
H4. Bloom density decreases in the *hours to days* following storm events. R4.1. Severe mixing events disrupt the buoyancy mechanisms used to maintain position in the water column (e.g., Walsby 1994, Sommer et al. 2012)
H5. **Blooms are more likely in the *weeks* following storm events.** R5.1. Storm events transport nutrients into lakes; localized increases are likely especially near stream inflows (e.g., Wetzel 2001, Sommer et al. 2012) R5.2. In deep water lakes that are anoxic below the thermocline, storms entrain hypolimnetic P into the water column (e.g., Soranno 1997)
H6. Bloom density is greater in ice-free lakes, and in lakes and years when the ice goes out sooner. R6.1. Longer stratification periods allow for greater bloom development (e.g., Reynolds 2003)
H7. Blooms spread from their initial points along the dominant wind direction and/or away from boat ramps. R7.1. Bloom spread across the lake is facilitated by wind and currents, boat traffic.

B. Phase 2: Synthesis and Modeling

The collected data will be integrated to combine different heterogeneous sensor measurements in a consistent way so that model-based and data-driven machine learning methods can be applied. While past work has had some success in predicting the severity of HCBs, we will develop ensemble prediction models to achieve high accuracy in split-sample cross validation (as opposed to the in-sample validation that seems to have been the focus of the bulk of past work (e.g., [38], [39], [40], [41], [42])). In particular, our ensemble models will merge ML methods with the Bayesian and structural equation modeling (SEM) approaches previously proposed by researchers studying HCBs. Part of our effort will investigate the temporal and geospatial scales at which accurate predictions can be made. First, we will test a host of ML techniques on a specific lake, then on regional lakes, and then on all lakes. Such new models will be used to validate a set of limnological hypotheses (Table I) that will help to shed light on the drivers of HCBs. This will adapt some of the strategies developed for the robot sampling.

C. Phase 3: Translation

While the proposed work will yield advances in robotics, limnology, and data science, we also aim to translate this research work into something that can be applied beyond our study systems. In particular, there are thousands of lakes in the U.S. that have issues with HCBs, and the available resources - human, equipment, and monetary - are insufficient for the needed monitoring and management. In this activity, we will use what we have learned in Phases 1 and 2 to develop recommendations for how the robots, high-frequency data, and modeling platforms might be used among citizen groups, not-for-profits, municipalities, and state and federal agencies. This will entail both the design of a low-cost flexible autonomous multirobot system tailored for more general use and the development of systems that will make the modeling more accessible to a wider audience.

III. DISCUSSION

The developed robotic systems with their potential of extending the current spatial and temporal scales of the collected data are essential for unraveling the drivers of where, when, and how cyanobacterial blooms develop and spread. To achieve this final goal, the research needs to be performed with a mindset oriented towards the problem rather than the method itself. This project raised several insights that can be driving principles in robotics research for environmental monitoring.

The problem itself is highly interdisciplinary, which requires the roboticists to have a deeper understanding of the current practice of limnologists, the parameters they are interested in, as well as some priors that can guide the robots to locations where to sample–for example considering linkages from watershed processes to the in-lake processes. One important part that sometimes is neglected in robotics research for environmental monitoring is sensor calibration and response time. The water quality sonde with, for example, a dissolved oxygen probe must be calibrated so that measurements can be related across systems and sampling events and can be interpreted by limnologists to test hypotheses. Such requirements might affect the development of sampling strategies as measurements might be affected by specific motions of the robot. Our team has already started field experiments this summer, where roboticists and limnologists designed joint studies and observed methodologies and approaches from each other to improve the overall process.

The designed robotic system needs to be robust, even in non-ideal conditions. For example, in New England, the experimental campaign will mainly happen during the summer, when there will be high boat traffic. The robots must continue to operate, so that the goal of collecting copious data is achieved. Robots need also to be easily deployed so that logistics associated with deployment is reduced, given the complexity of coordination across the many sampling methodologies. This has been the design principle for the custom-made boat at Dartmouth which can be carried and deployed by a single person (Fig. 3 (top)). An alternative ASV design [43] enabling longer operational times can be seen in Fig. 4 during multi-robot coverage operations [44].

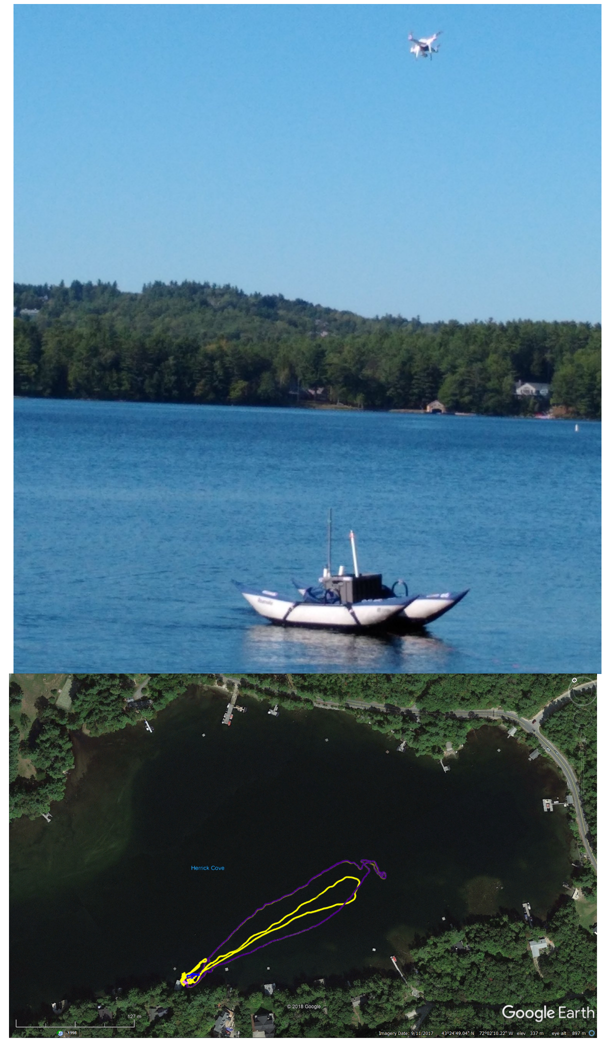


Fig. 3: Preliminary experiments with a boat and drone at Lake Sunapee, NH, in collaboration with the Lake Sunapee Protective Association, and a transect where traditional sampling (manual and buoy) is combined with a robot.

The research community should not be the only one involved in such an effort. Citizen scientists who live around the lakes can be a powerful resource as well for several reasons, and they should be included in the first phases of the project. First, they can provide invaluable insights given their daily observations. Second, they can provide logistical support and increase the number of deployments and, as a result, the amount of data that we can collect and the models we can train. Toward this end, our team is working closely with water quality preservation and management associations in all states. This summer we completed initial deployments of a custom-made robotic boat together with a drone with the Lake Sunapee Protective Association (see Figure 3).

Eventually, we plan to scale this project up so that the developed technologies can be used by lake managers and citizens to monitor and protect the freshwater lakes beyond our boundaries.

Fig. 4: Deployment of three custom made ASVs for covering a large area.

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