Multi-Modal Lake Sampling for Detecting Harmful Algal Blooms

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***Abstract*— In this paper, we present a system for measuring water quality, with a focus on detecting and predicting Harmful Cyanobacterial Blooms (HCBs). The proposed approach includes stationary multi-sensor stations, Autonomous Surface Vehicles (ASVs) collecting water quality data, and manual deployments of vertical water sampling together with vertical water quality sensor data collection, in order to monitor the health of the lake and the progress of different types of algal blooms. Traditional water monitoring is performed by manual sampling, which is limited both in the spatial and the temporal domain. The proposed method will expand the range of measurements while reducing the cost. Human sampling is still included in order to provide a base of comparison and ground truth for the automated measurements. In addition, the collected data, over multiple years, will be analyzed to infer correlations between the different measured parameters and the presence of blooms. A detailed description of the proposed system is presented together with data collected during our first sampling season.**

I. Introduction

This paper proposes a multi-modal monitoring system for monitoring Harmful Algal Blooms (HABs) in surface fresh waters, such as lakes and reservoirs – see Fig. 1. Habs occur in fresh, salt, and brackish waters, that is, in lakes, marine, and estuarine environments. They are the result of many different organisms, such as toxic and noxious phytoplankton, macroalgae and benthic algae, and cyanobacteria. In fresh water environments, such as lakes, are mainly caused by benthic algae and cyanobacteria, thus often called Harmfull Cyanobacteria Blooms (HCBs). Since 2010 there have been more than 500 reports in USA of harmful blooms[1].

Since the seventies [1] scientists are trying to monitor, understand and predict algal blooms, a topic that has stayed an active area of research. Remote sensing [2] from satellite images was utilized to observed lakes, albeit in low resolution. The environmental drivers that initiate, maintain, and influence the growth and spread of HCBs are still not fully understood, which impedes their predictability and management. Traditional science relies on manual sampling of the water in distinct locations. This process is labor intensive, time consuming, often exposes scientists to unsafe conditions (contact with toxic algae), and is limited both spatially and temporarily. However, manual sampling/data-collection is the standard approach and provides an excellent starting point and a base of comparison. Within the robotics community, work that could be applicable for this task includes algorithms for coverage of a known environment [3]–[5] or adaptive sampling [6], [7]. Such approaches are still largely underused in practice; their focus is on minimizing the task cost (e.g., traveled distance) rather than evaluating the system as a whole for high-quality data collection.

Fig. 1: Autonomous Surface Vehicle collecting bathymetric and water quality data around a permanent sensing station.

In this paper, as part of a larger effort in the US East Coast [8], [9], the proposed approach utilizes the traditional data collection methods, augmented with autonomous operations. In particular, we have identified two man-made impoundment lakes of significant size in South Carolina that exhibit algal growth. In both lakes, municipal and state actors have been collecting water quality data for years. We built upon this work by introducing a complete water sampling system. Central in the proposed approach is an Autonomous Surface Vehicle (ASV) [10] equipped with a YSI EXO2 multi-sensor sonde for collecting water quality data near the lake surface over large areas. In addition to the ASV operations, two buoys are placed in each lake, collecting dissolved oxygen and temperature data at different depths at high frequency (every 10 minutes) all year round. Finally, during the growth session (April to October) manual water sampling with a Niskin bottle together with vertical deployments of a second multi-sensor sonde are performed in distinct locations every two weeks. We evaluate a boustrophedon and a spiral coverage patterns. The main contribution of this paper is in providing guidelines on reliable and efficient collection of data that can be used then for training predictive models and

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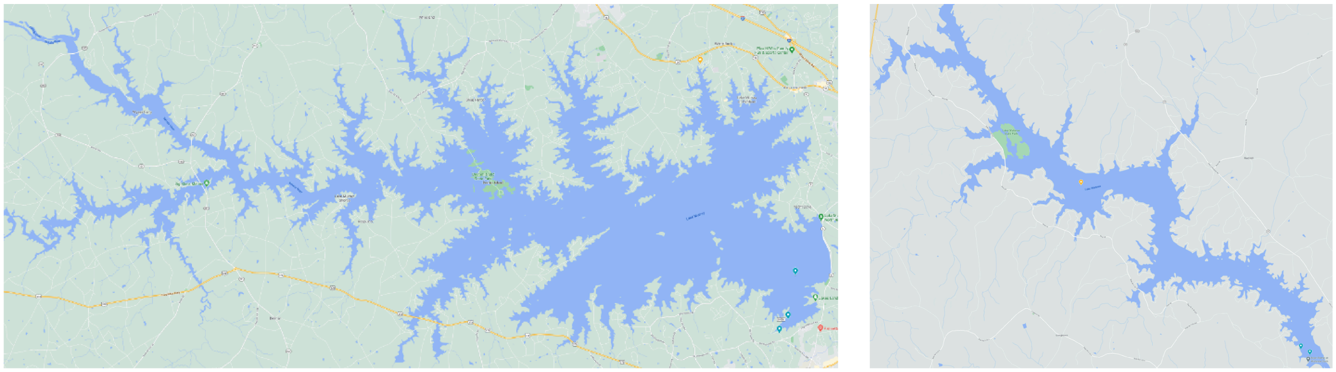
[1]https://www.ewg.org/interactive-maps/algal_blooms/map/



(a)

(b)

Fig. 2: (a) Lake Murray. (b) Lake Wateree. South Carolina, USA. From: `https://www.google.com/maps/`

informing stakeholders of the lake health. Lessons learned from one-year data collection will be provided for such a long-term deployment.

The rest of the paper presents the details of the proposed approach, the rationale behind the design decisions, and lessons learned from the first year of deployments.

II. Related Work

Work in the limnology literature that studies predictive models for the occurrence of HCBs [11]–[15] relies on datasets from sources that are typically considered independently. For example, manual sampling within each lake at weekly or monthly intervals [16], [17]; buoys deployed in fixed locations that can measure water parameters at minute or hour intervals [18]; and satellite imaging [19]–[21]. With such data collection approaches, the spatial coverage or the resolution of the data is limited, stifling the advances in the understanding of HCBs.

Robotic systems can allow scientists to collect datasets with higher spatial coverage and resolution. One main family of data collection methods is based on *coverage* [22], [23]. The traditional approach is to employ a boustrophedon path to fully cover the free space of the region with a sensor. A number of methods have been proposed to optimize the coverage cost for a single robot (e.g., [5], [24]–[27]) or multiple robots (e.g., [3], [4], [28]–[32]). If some prior information is available, selective coverage methods [33]–[36] are employed. This body of research focused on the same type of sensor capabilities. A second type of approaches is based on *adaptive sampling*: take measurements only in "interesting" locations – e.g., where there are high hotspots – with the model built online. Valada *et al.* [37] developed a low-cost multi-robot autonomous platform for monitoring water quality, by discretizing the area and selecting locations based on maximum uncertainty. Girdhar *et al.* [38] demonstrated a heterogeneous multi-robot system consisting of a UAV, an ASV, and an AUV to cover an area of interest indicated by a human expert. Low-cost assets are sometimes used to collect lower resolution data and inform more expensive vehicles for higher-resolution data [6], [7], [39]. In general, the focus of this set of work from the robotics community is on efficiency. The long-term aspect and the reliability of the data from different sensors and their integration is still an open problem.

To enhance the data available for predictive models and interception efforts of HCBs (e.g., from the U.S. Army Engineer Research and Development Center (ERDC) [40]), we present a holistic system composed of stationary sensors and ASVs and the long-term data collection performed during our first year.

[41]

[42], [43]

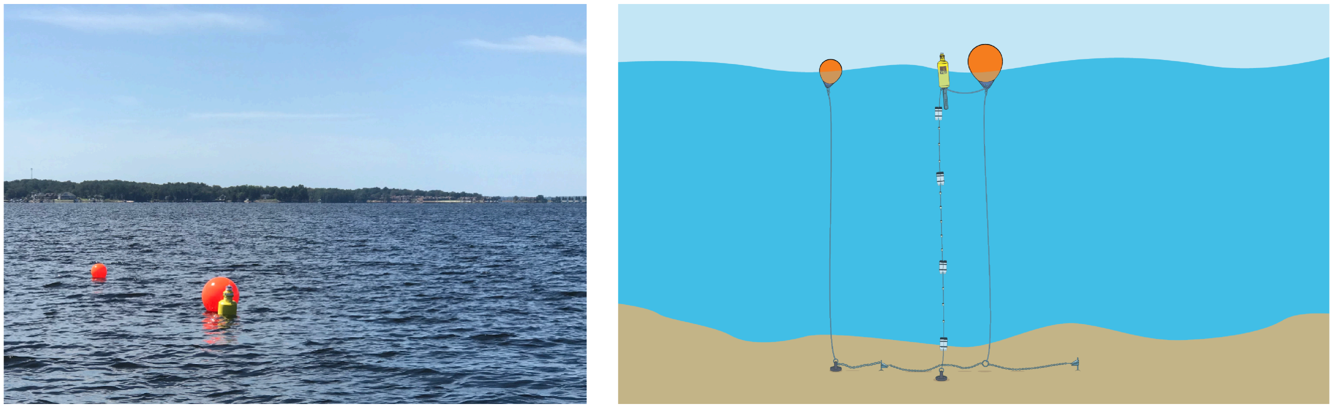
III. The Proposed System

A. Overview

The proposed approach includes several different sensors deployed in a variety of methods in order to collect water quality measurements. Four different buoys have been deployed, two on each lake, covering a shallow and a deep station near water intakes for two different water treatment plants. These four station operate year-round collecting dissolved oxygen and temperature data at different depths, at high temporal frequency, and they provide a baseline on the conditions of each lake. Autonomous Surface Vehicles (ASVs) [10] have been equipped with a YSI EXO2 multiparameter sonde [44] to collect water quality samples near the surface (at $0.5\,\mathrm{m}$ depth) utilizing different (horizontal) sampling patterns. In addition, bathymetry data are collected and the water quality data are augmented with the depth information along the trajectory of collection. In addition, a second multiparameter sonde is manually deployed for collecting vertical profiles at select locations together with water samples at distinct depths for laboratory analysis, at a low temporal frequency (every two weeks). The resulting system obtains data in three dimensions at distinct time instances and continues samples in select locations.

B. Target Environment

The proposed system is expected to be deployed in different water bodies wherever harmful blooms occur. In South Carolina, we have selected two lakes: Lake Murray (Fig. 2(a)) and Lake Wateree (Fig. 2(b)). Lake Murray spans



(a) (b)

Fig. 3: (a) The deep water station at Lake Murray. (b) The station setup ensures stability, even during extreme weather events.

more than $200\,\mathrm{km}^2$, has a shore length in excess of $700\,\mathrm{km}$, with a length of $66\,\mathrm{km}$ and with a maximum depth of $57\,\mathrm{m}$. Lake Wateree covers an area of $49\,\mathrm{km}^2$, with a shore length of $291\,\mathrm{km}$, and a maximum depth of $19.5\,\mathrm{m}$. Both are man-made impoundment lakes, used for municipal water supply and recreation. They are subject to extensive nutrient loading and experience reoccurring poorly resolved HCBs that are dominated by the toxin producing cyanobacteria Microcystis aeruginosa in Lake Murray and the benthic cyanobacterium Lyngbya wollei in Lake Wateree [45], [46].

C. High Temporal Frequency Vertical Sensing

Two monitoring stations collecting vertical water-column measurements of dissolved oxygen and temperature are placed in both lake Murray and lake Wateree. For both lakes, the water enters from one side and exits on the opposite side. These stations obtain vertical profiles at one shallow and one deep place in each lake. The shallow stations are located close to the drinking water intake in each lakes. In addition, the deep stations are placed near the outflow of the lake. In both lakes the placement of the four stations can be seen Fig. 2 in the lower right part.

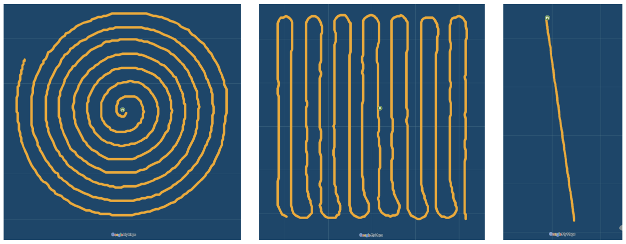
The stations utilize the miniDOT [47] sensor in conjunction with an anti-fouling wiper [48] to measure dissolved oxygen and temperature. The accuracy of the dissolved oxygen measured optically, is $\pm 10\,\mathrm{\mu mol/L}$, while the accuracy of the temperature measurements is $\pm 0.1\,°\mathrm{C}$. The sampling interval is set to ten minutes and the data are stored internally on the sensors. It is worth noting that, due to the water condition and the long duration of deployment, the use of an anti-fouling wiper is necessary to remove growth of biological organisms from the sensor. Additional miniature one-channel temperature data loggers (HOBO 64K Pendant sensors from Onset) [49] are used to record the water temperature with the sampling interval set to ten minutes and the data stored internally. The accuracy of the temperature sensor is $\pm 0.53\,°\mathrm{C}$. The data are collected by manually retrieving the line with the sensors and then individually downloading the data to a computer. After removing the measurements that occurred while the sensors were outside the water, the data are made available online for the scientific community and the general public.

The proposed multi-sensor station setup is designed to maintain a secure placement even in the event of extreme weather. South Carolina is often visited by hurricanes, while the target lakes are further inland, severe rainfall and strong winds are common. The YSI EMM25 buoy is used to secure the string of sensors on one end, at the other end a $4.53\,\mathrm{kg}$ mushroom anchor keeps the line from drifting. The YSI buoy is connected to a large orange buoy that provides a stable platform; see Fig. 3(a) for a picture of the three surface buoys. The large orange buoy is connected to two Danforth fluke anchors at the bottom which they grip the bottom and are extremely difficult to move. One of the Danforth anchor is connected via a chain to a second $4.53\,\mathrm{kg}$ mushroom anchor which is connected to the smaller orange buoy at the surface. Please refer to Fig. 3(b) for a diagram of the buoy/anchor setup. The smaller orange buoy can be used to raise the mushroom anchor, pulling the connected (first) Danforth anchor, which will pull the second Danforth anchor for relocating the station.

The sensor placements in each station is designed to measure dissolved oxygen near the surface and near the bottom: $1\,\mathrm{m}$ from the water surface and $1\,\mathrm{m}$ off the bottom; and in equal distance in between. More specifically, in lake Murray, the deep station is at a depth of $30\,\mathrm{m}$ and is equipped with four miniDOT and 11 HOBO sensors; the shallow station, at $6\,\mathrm{m}$, has two miniDOT and two HOBO sensors. Lake Wateree: the deep stations is at a depth of $17\,\mathrm{m}$ with three miniDOT and eight HOBO sensors, while the shallow station at $6\,\mathrm{m}$ has the same configuration as the shallow station at lake Murray.

D. Low Temporal Frequency Horizontal Sensing

The proposed approach utilizes a YSI EXO2 multiparameter sonde [44] equipped with a suite of sensors measuring depth, temperature, conductivity, dissolved oxygen, pH, turbidity, and total algae/phycocyanin. The sonde is mounted $0.75\,\mathrm{m}$ below the waterline on an Autonomous Surface Vehicle (ASV) [10] collecting data every two seconds.



(a) (b) (c)

Fig. 4: GPS coordinates of deployed patterns recorded by PixHawk on $151\,\mathrm{m}{\times}151\,\mathrm{m}$ area with $10\,\mathrm{m}$ sensor footprint ASV. Green landmark point is the location of deep station. (a) Spiral, and (b) Boustrophedon, c) $1.076\,\mathrm{m}$ Single line transect.

The ASV is controlled by a low-level controller, the 3DR Pixhawk running a realtime operating system, NuttX OS, in combination with the ArduPilot s/w suite. The Pixhawk utilizes internal/external compass and an external GPS. After installing the GPS, the compass (both internal and external) are calibrated and the coordinate transformation between the GPS and the Pixhawk is calculated. The PixHawk is set to Rover configuration thus the steering and throttle servos of the ASV are directly controlled by modifying the Pulse Width Modulation (PWM) values in the PixHawk to match the vessels operating specifications. The vehicle is also equipped with a bathymetric sonar: either a single ping sonar (NMEA 0183 CruzPro AT120-P) or a side scan sonar (Humminbird Helix 7). Processed data from the side scan sonar are presented in Section IV. The autonomous vehicle collects time-stamped data, ROS bagfiles [50], correlating the GPS locale, the bathymetry, and the water quality data.

Different trajectory generation strategies are employed in order to guide the ASV. Of particular interest are the regions around the buoy deployments, across each lake, and the data variance near shore and in the middle of the lake. Transects at different locales produced water quality data correlated with the bathymetric morphology. In addition, two different strategies: a spiral pattern and a boustrophedon pattern have been utilized to investigate the variation in the chlorophyll values around the testing stations; see Fig. 4 for two sample trajectories along with a sample transect. The patterns have been deployed several times on $100\,\mathrm{m}{\times}100\,\mathrm{m}$ and $151\,\mathrm{m}{\times}151\,\mathrm{m}$ areas around the deep station with an ASV's sensor footprint of $10\,\mathrm{m}$. A comparison of the distance traveled and area covered in the two patterns is presented in Table I. The experiments show that there is only slight difference between boustrophedon and spiral patterns in terms of distance traveled, area covered and time. This can be explained by the fact that in a curved trajectory what is gained in the wider end is lost from the narrower end. For example, in the coverage of a part of an annulus, the inner circle is shorter by the same amount that the outer circle is longer, as compared to the middle. It is worth noting that, when deploying to cover a small area around a point of interest, the spiral pattern is more applicable. When a rectangular patch needs to be covered, given the ASV turning radius constrains, for smaller footprints, the Dubin's vehicle coverage method is required [5].

	Spiral	Bsd	LSpiral	LBsd	Line
Time	6m 29s	7m 46s	15m 58s	17m 55s	8m 29s
Len.	745 m	869 m	1915 m	2173 m	1076 m
Area	$7451m^2$	$8689m^2$	$19150m^2$	$21730m^2$	$10760m^2$

TABLE I: Comparison of the coverage metrics for different ASV patterns. Spiral and Bsd refer to spiral and boustrophedon patterns covering an $100\,\mathrm{m}{\times}100\,\mathrm{m}$ area, while LSpiral and LBsd refer to the same patterns covering an $151\,\mathrm{m}{\times}151\,\mathrm{m}$ area respectively.

E. Low Temporal Frequency Vertical Sensing

As part of our sampling program, we collect vertical profiles with a second YSI EXO2 sonde, with the same sensors as the one mounted on the ASV. In the first phase, deployments have been conducted at the shallow and deep stations at both lakes. The data collected provide a more nuisance image of the state presented by the permanent sensing stations discussed above. Furthermore, correlations between the chlorophyll values and temperature and dissolved oxygen are considered; it is worth noting the permanent stations only record temperature and dissolved oxygen.

F. Low Temporal Frequency Vertical Sampling

We collect water samples at 3–$5\,\mathrm{m}$ depth intervals for nutrient analysis at each station location using a Niskin bottle. Nutrient samples (nitrate, nitrite, ammonium, phosphate as well as dissolved organic nitrogen and phosphorus) are analyzed in the Bourbonnais Lab at UofSC using a Seal Analytical AQ300 nutrient autoanalyzer. Samples for chlorophyll a and phytoplankton community composition analysis by high performance liquid chromatography are also collected at the same depths (collaboration with Dr. James Pinckney, University of South Carolina).

IV. Experiments

The above described multi-modal data collection provides a diverse set of data covering different areas of the lakes over extended periods describing different facets of the water conditions. Starting with traditional marine science manual operations, Fig. 5 shows depth profiles collected within approximately a two-week interval in September/October 2020 at the deep and shallow stations in lake Murray. Chlorophyll maximum was around two-meter depth at all stations. pH decreased toward deeper waters due to net carbon dioxide production coming from the respiration of organic material. Oxygen depleted bottom waters were observed at the deep station due to oxygen consumption during respiration. We observed weaker stratification and deepening of the oxic/anoxic interface over time, which is expected as temperature and densities of the different water masses become more similar as fall progresses.

From the water samples collected in both stations in lake Murray the laboratory analysis showed that, nitrate, nitrite and phosphate were completely depleted (i.e., below method detection limits) at all depths at both the shallow and deep stations (data not shown). Ammonium was depleted

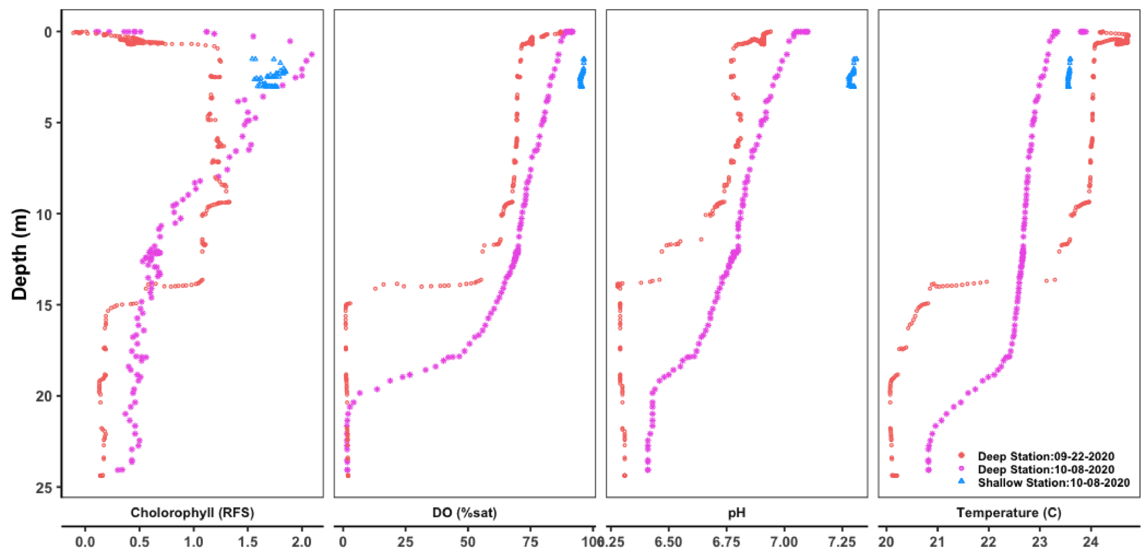


Fig. 5: Vertical profiles of chlorophyll, dissolved oxygen, pH, and temperature in Lake Murray collected with the YSI EXO2 sonde.

in surface waters and at the shallow station but gradually increased to up to about $0.1\,\mathrm{mg/L}$ in hypoxic bottom waters at the deep station (Table II).

Sampling date	Station	Depth (m)	NH_4^+ concentration (mg/L)
09/15/2020	Shallow	1	0
09/15/2020	Shallow	4	0
09/22/2020	Deep	4	0
09/22/2020	Deep	25	0.0736
10/8/2020	Shallow	1	0
10/8/2020	Shallow	4	0
10/8/2020	Deep	5	0
10/8/2020	Deep	12	0.0196
10/8/2020	Deep	17	0.0248
10/8/2020	Deep	25	0.1138

TABLE II: Laboratory analysis results for NH_4^+ concentration, from water samples collected in lake Murray.

The results from the two permanent stations provide a profile of the temperature and dissolved oxygen at different depth. Figure 6 shows that the lake was stratified until late October and then completely mixed during fall and winter. This is clear from the top row of Fig. 6 where the temperature from the miniDOT and HOBO sensors is stratified at the beginning to converge to a slowly lowering temperature over time as the weather gets colder. The dissolved oxygen, presented in Fig. 6(c), is between 80%-100% near the top of the lake and a bit lower at $9\,\mathrm{m}$, however it is quite depleted at $20\,\mathrm{m}$ and the environment is anoxic near the bottom at $30\,\mathrm{m}$. As the waters mix during fall, all the values converge. It is worth noting, the miniDOT data is consistent with the YSI vertical profiles from Fig. 5.

During deployment of the ASV, the YSI EXO2 data are correlated with the GPS location at the time of collection and the water depth at that location. During deployments two area coverage patterns were used (see Fig. 4) the data from the side scan sonar were processed to provide a bathymetric map. Figure 7 presents the two maps around the deep station. As can be seen, the bottom varies from $22\,\mathrm{m}$ up to $36\,\mathrm{m}$ inside the $151\,\mathrm{m}\times151\,\mathrm{m}$ area.

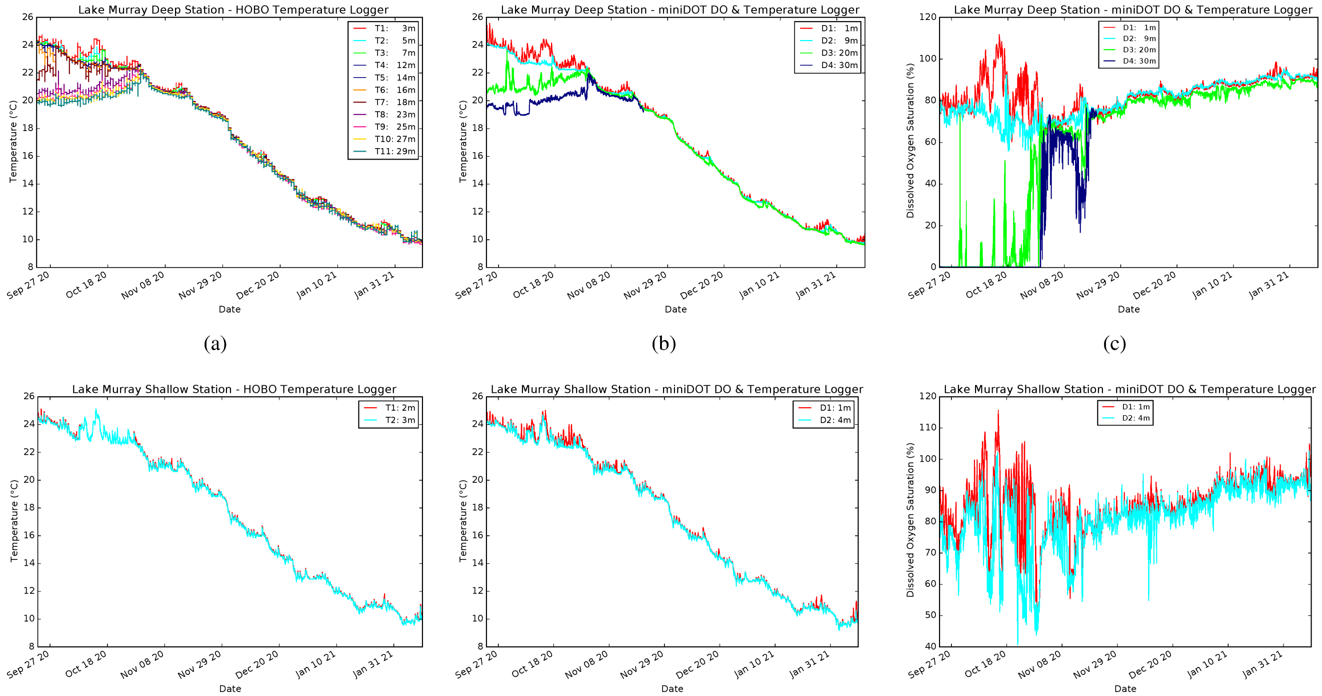
V. Lessons Learned

Over the past year we have deployed four multi-sensor stations, equipped an ASV with a sonde, and collected data and sample both autonomously and manually. The data collected have demonstrated that the horizontal variation is limited, thus an automated system for deploying the sonde at different depths will be critical. Furthermore, the manual data acquisition from the four stations introduces a lag. Producing a wireless data collection setup will be extremely convenient, however, it is prohibitively expensive. In addition, one of the challenges faced is the disappearance of some of the sensor stations hardware. Deploying, unattended over a long time (months), buoys at a popular lake has resulted in some of the buoys to disappear. Future work will consider better theft-proof attachment methods.

VI. Conclusion

A large scale sensing and sampling operation is proposed in this paper. Traditional marine science methodology is augmented with autonomous sensing approaches in order to collect large volumes of data extending both temporally and spatially. Proper data acquisition, labeling, and management are critical in order to infer correlations between different quantities measured enabling the prediction of harmful algal blooms.

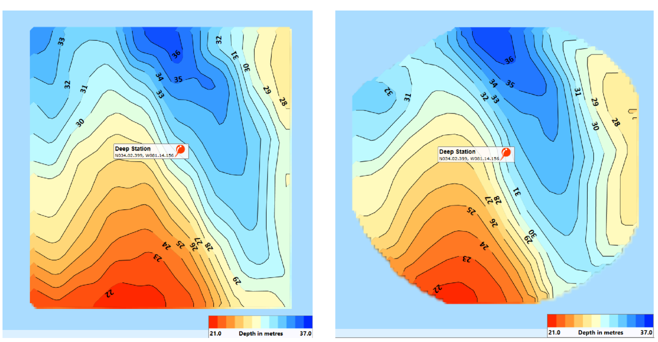
Future work will involve resource constraint water body coverage [42][43] and multiple ASVs operating simultaneously, either following different strategies or coordinating in order to cover much larger areas [4]. Due to the large surface of the target lakes, scaling up to multiple ASVs will be necessary when a complete survey of the lake is required. Otherwise, heterogeneous teams of ASVs can be deployed to identify areas of increased algal activities, where a second ASV or a human operator will collect samples [6].



(a) (b) (c)

(d) (e) (f)

Fig. 6: **Top row**: Lake Murray Deep station. (a) Temperature measurements from 11 Onset HOBO sensors; (b) Temperature measurements from 4 miniDOT sensors; (c) Dissolved Oxygen Saturation Percentage from 4 miniDOT sensors. **Bottom row**: Lake Murray Shallow station. (d) Temperature measurements from 2 Onset HOBO sensors; (e) Temperature measurements from 2 miniDOT sensors; (f) Dissolved Oxygen Saturation Percentage from 2 miniDOT sensors.



(a) (b)

Fig. 7: Bathymetric map, lake Murray (a) Boustrophedon pattern. (b) Spiral Pattern.

Aerial observations will provide additional information utilizing a hyperspectral camera. Extending the marsupial system presented by Kalaitzakis *et al.* [51], where an Unmanned Aerial Vehicle (UAV) takes off and lands on an ASV, by using a UAV capable of landing on water; see Fig. 8, will generate a robust setup even in the case of a water landing. In particular, hyperspectral imaging can be used to detect algal blooms near the surface [52], [53], utilizing the water quality data collected by the ASV, when a bloom is detected the UAV will take off, and map the extent of the bloom by flying around the ASV.

Fig. 8: The HexH2O hexacopter landing on water.

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[2]https://sites.google.com/view/dallage

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