Towards a Reliable Heterogeneous Robotic Water Quality Monitoring System: An Experimental Analysis

Monika Roznere*[1], Mingi Jeong*[1], Lily Maechling[1], Nicole K. Ward[3], Jennifer A. Brentrup[4], Bethel Steele[5,6], Denise A. Bruesewitz[7], Holly A. Ewing[5], Kathleen C. Weathers[6], Kathryn L. Cottingham[2], and Alberto Quattrini Li[1]

[1]Dept. of Computer Science, [2]Dept. of Biological Sciences, Dartmouth College; [3]Dept. of Biological Sciences, Virginia Tech; [4]Dept. of Biology and Environmental Studies, St. Olaf College; [5]Environmental Studies Program, Bates College; [6]Cary Institute of Ecosystem Studies; [7]Environmental Studies, Colby College

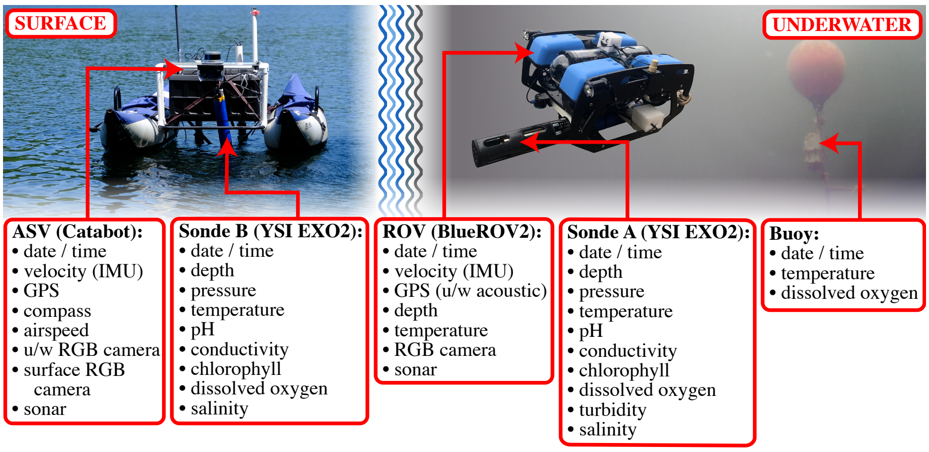


Fig. 1: The instrumentation and parameters that make up the sensor system come from three sources: an ROV, an ASV, and a sensored underwater buoy.

1 Problem Statement, Motivation, and Related Work

This paper describes experiments that tested the effect of robotic movement on the reliability of aquatic sensor readings. It also demonstrates the utility of a heterogeneous system of robots to advance limnological monitoring and research. An Autonomous Surface Vehicle (ASV) and an underwater Remotely Operated Vehicle (ROV), both equipped with multiparameter water quality sondes, were deployed weekly in Lake Sunapee, NH, to collect routine measurements horizontally over the water surface and vertically in the water column, respectively. We

* These authors contributed equally to the paper.

Presented at the International Symposium on Experimental Robotics (ISER) 2020.
DOI: 10.1007/978-3-030-71151-1_13

then compared the robot-collected data with data from fixed underwater instrument platforms (buoys) outfitted with a complementary suite of sensors as well as manually collected samples. The ASV was also deployed on one date in China Lake, ME, to test robotic procedures and evaluate potential environmental effects, including heterogeneity in water quality. We found that sensor response time and robotic movement (e.g., turns, stops, collisions) produced small discrepancies between the robot-derived and other datasets. Further, robotic coverage patterns impacted water quality parameter measurements, affecting our understanding of horizontal heterogeneity in biological and chemical data across the lake surface.

A principal goal of aquatic monitoring is to provide data which can be used to inform protection of and management of good water quality for drinking or recreation. However, the limited spatial and temporal coverage of traditional limnological monitoring may constrain inferences about water quality. For example, monitoring typically involves measuring water clarity, temperature, dissolved oxygen, nutrients, and biological variables such as chlorophyll-a, at weekly to monthly intervals, usually during the ice-free season, at a single site. Although continuous sensor measurements on fixed-location buoys has increased temporal sampling frequency of many variables [15], the number of buoys in a lake and type/number of sensors are typically limited by cost constraints, thus limiting spatial coverage. Moreover, buoy locations and depth of sensors are often selected based on discretized zones, such as pelagic (open water) areas or above and below the thermocline [12]. However, heterogeneity within commonly accepted lake zones is increasingly being recognized as critical for understanding lake ecosystem functioning [12]. We therefore seek to monitor the key factors that drive water quality by collecting and integrating higher spatial and temporal resolution data using autonomous vehicles.

A limnology-computer science interdisciplinary approach of designing sampling strategies for ASVs and underwater ROVs within robot-based limitations is a promising method to monitor waterbodies more effectively [3,9,10,13]. Two types of robotic approaches have been used: *complete coverage* and *adaptive sampling* [2]. *Coverage approaches* are based on area decomposition to identify unit cells covered with a specific motion (e.g., lawnmower pattern) and on optimization techniques to order the cells to visit, which minimizes a cost function (e.g., traveled distance) [1,6,11]. For example, Garneau *et al.* [7] used an ASV to collect high resolution water quality data, but due to the slow response time of the dissolved oxygen probe, the coverage was limited only to a 2D transect line across a lake. As an alternative, *adaptive sampling techniques* process real-time sensor data strategically visiting spots of high interest [4,5]. Hitz *et al.* [8] extended their earlier work [7,9] with a 3D real-time planner for an ASV that continuously collects data at different sensor depths while traveling to pre-established waypoints. They did not use a dissolved oxygen sensor, removing the limitations enforced on robotic speed. These prior studies highlight that research is needed to better understand how robot movement may interact with sensor characteristics to impact data quality and bridge the gap for implementing effective and reliable sampling methods in real-world environments.

We address the following questions:

- How do robotic motions affect water quality sensor response time?
- How do water quality measurements compare between robots and fixed-location buoys?
- How can robotic coverage paths best complement and extend monitoring data from discrete water samples (i.e., chlorophyll-a concentrations)?

The main contribution of this paper is to provide insights that will improve *robotic sampling* techniques for collecting reliable sensor data, thereby providing higher resolution temporal and spatial information about water quality.

2 Experimental Methodology and Setup

Our integrated system for water quality data collection is illustrated in Fig. 1. The system includes the following robots:

- BlueROV2: An underwater ROV with downward-looking sonar, front-facing RGB camera, acoustic transducer for short baseline localization, and YSI EXO2 sonde (Sonde A) recording water temperature, depth, pH, conductivity, chlorophyll fluorescence, dissolved oxygen (DO), salinity, pressure, and turbidity at 1 sec intervals;
- Catabot [10]: An ASV with sonar, surface and underwater RGB cameras, GPS, anemometer, and Sonde B (similar to Sonde A, but no turbidity sensor).

The weekly robotics experiments reported here occurred at Lake Sunapee, NH, from ice-out in April until September 2020. We were particularly interested in comparing robotic water quality measurements to existing limnological data:

- Winter Buoy: A fixed, instrumented, subsurface buoy (44 m from the home location in Fig. 6) with sensors along its vertical line ($1-8$ m). Dissolved oxygen (DO) was measured at two depths (1 and 8 m) at 10 min intervals using PME Mini-DOT loggers. Water temperature was measured every $0.5-1$ m along the full vertical profile at 2 hr intervals using HOBO pendant temperature loggers;
- Summer Buoy: A fixed, instrumented, surface buoy (313 m from the home location in Fig. 6) with the same sensors along its vertical line as the Winter Buoy. Here, we focus on the PME Mini-DOT sensor at 1 m depth that measured water temperature and DO at 10 min intervals;
- Hand-collected water samples (grab samples) that were subsequently analyzed for chlorophyll-a [14].

In this analysis, we compare vertical data on temperature and DO from the ROV to the Winter Buoy, and surface measurements of temperature, DO, and chlorophyll-a made by the ASV near the Summer Buoy and home location.

We also evaluated the effect of sensor response time and field conditions on data quality at Lake Sunapee and China Lake, ME. In the laboratory, we measured sensor response time defined as the time to equilibrium for temperature and DO when moving between buckets of hot (40 °C) vs. cool water (20 °C) or still vs. bubbled water. These times were then compared to field measurements in which the ROV traveled vertically along the Winter Buoy line, stopping at individual sensor locations for set amounts of time. For the ASV, we analyzed sensor response time and instability by internal factors – when it moved (with linear and angular motion) and stopped in one place or continued to move to waypoints during a path coverage – and external factors – when it encountered adversarial environmental conditions. We also quantified the impact of the ROV hitting bottom and stirring up the sediment on sensor readings.

Finally, we determined how different ASV coverage paths inform the adequacy of sampling spatial resolution relative to spatial variability in water quality variables within the environment at both Lake Sunapee and China Lake. At Lake Sunapee, the ASV took three lawnmower path patterns (see Fig. 6) with overlap to gain better spatial distribution: 1) *Black* path – vertical lawnmower, 2) *Blue* path – diagonal lawnmower, and 3) *Red* path – quadrilateral. We determined the principal direction of the paths by avoiding dominant adversarial external conditions, i.e., wind (from *NW*) and current (towards *SE*) to attain motion efficiency and sensor reliability from our previous study [10]. The three paths were executed in the following order: 1) *Black*, 2) *Blue*, and 3) *Red*.

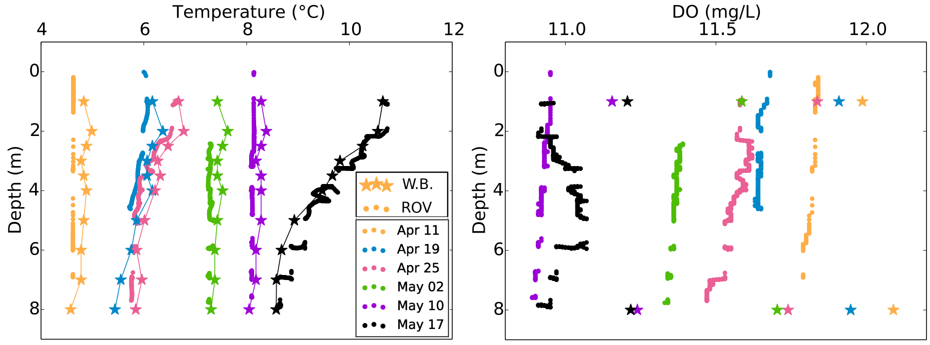
3 Experimental Results and Analysis

Our experiments revealed (1) effects of sensor characteristics and robot motions on sonde readings; (2) small differences between data collected with the robots and those collected from stationary buoys or via grab samples; and (3) a measure of spatial heterogeneity of water quality measurements as compared to grab samples.

3.1 Sensor response times and robot motions have a modest impact on sensor reliability

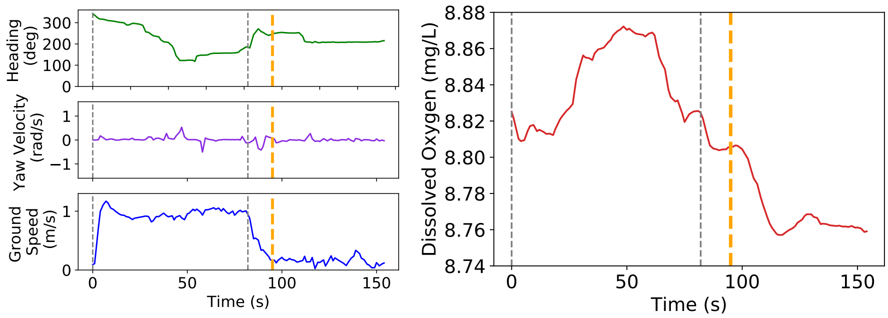
Sensor response times under controlled scenarios (i.e., hot-cold, still-bubble) averaged 26 sec (3.4 sec standard deviation [SD]) for temperature (°C) and 27 sec (4.3 sec SD) for DO (mg/L) to achieve a stable reading. Although these two times are very similar, the proportional temperature differential was greater than that for DO, suggesting that DO readings take slightly longer time to stabilize for a given differential. This is expected, as optical-based sensors have slower response times than electrical sensors. For reference, temperatures are unlikely to change more than 5 °C over 0.5 m, whereas DO can change drastically from $4 - 6$ mg/L to < 2 mg/L over the same water column.

To compare these response times to those in real environmental conditions (see Fig. 2), the ROV collected data as it moved vertically along the buoy line and stayed at each depth associated with a sensor on the buoy for 1 min. In these profiles, temperature and DO measurements from the ROV sensors stabilized after about $10 - 15$ sec, as indicated by SD below 0.01. Each sensor's response time is not only based on the *type of sensor* it is, but also the current *variability of the environment* (i.e., change in the variable being measured over area or depth). For example, the onset of thermal stratification by May 17 meant that both temperature and DO now changed with depth. In comparison with the nearly isothermal conditions in previous weeks, the ROV control would need to



(a) **(b)**

*Fig. 2: ROV with Sonde A (points) vertical profiles compared to fixed-location Winter Buoy sensors (star) at Lake Sunapee, NH. **(a)** Temperature (°C) measurements match well. On May 17 (black), the ROV captured the beginning of thermal stratification. **(b)** DO* (mg/L) *measurements also agree – values are within known measurement error. Note, the DO range is very small. The results reinforce the need for higher resolution data throughout the water column.*

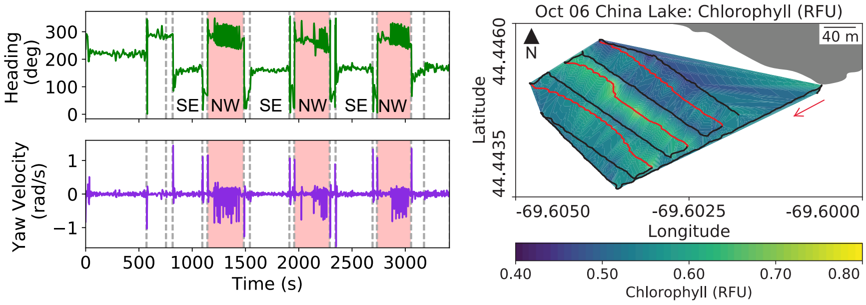


(a) **(b)**

*Fig. 3: ASV deployment at Lake Sunapee, NH on June 17. **(a)** Proprioceptive data of ASV. **(b)** Measurements of surface water DO* (mg/L)*. After the ASV initiated and finished motion (between two gray dashed vertical lines;* 0 sec *and* 82 sec*), it completely stopped in one place starting at* 95 sec *(orange dashed vertical line). DO measurements took about* 30 sec *to stabilize after the ASV ceased movement.*

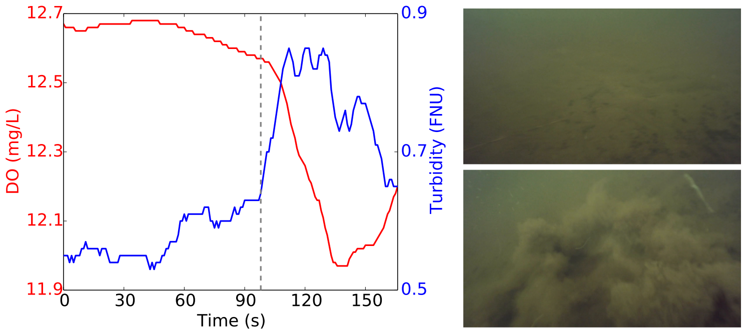
actively be aware of how readings change with a given depth and pause longer at specific depths when needed. Furthermore, water movement (e.g., due to wind or currents) and required ROV motion (e.g., depth hold) caused some fluctuation in sonde readings, even after readings had stabilized.

For the ASV, two main factors affected sensor stability during a path coverage: *motion attributes* (internal) and *environmental conditions* (external). First, rotational and translational movement at each waypoint may delay sensor responses. For example to monitor the sensor reading stability, the ASV arrived at home location at 82 sec and stayed in one place at 95 sec to monitor the sensor reading stability (Fig. 3). The DO sensor readings stabilized after ap-



(a) **(b)**

Fig. 4: ASV deployment at China Lake, ME on October 6. ***(a)*** *Proprioceptive data of ASV. The red shaded areas indicate when ASV adjusted its heading to counteract external forces while following the NW direction.* ***(b)*** *Coverage paths and measurements of surface water chlorophyll (RFU) linearly interpolated across an area of* $0.04\,\mathrm{km}^2$*. The red tracks indicate the same time intervals as the shaded area in (a). The red arrow is the starting direction.*



(a) **(b)**

Fig. 5: ROV deployment at Lake Sunapee, NH. ***(a)*** *The ROV hit the bottom of the lake and stirred up sediment around* 100 sec*. Sonde A's turbidity sensor (FNU) detected an increase in sediment particles, and a few seconds later the DO* (mg/L) *readings dropped.* ***(a)*** *Before and after underwater images from the ROV.*

proximately 30 sec, indicating that the previous motion of the ASV impacted sensor readings. Second, environmental conditions independent of ASV movement can alter the ASV path (e.g., primarily when following the NW direction in Fig. 4), which may also affect the sensor reliability. When the ASV adjusted its heading to counteract external forces (Fig. 4 (a) – red shaded area), the motions caused higher variability in DO measurements, in particular between 2736 −3051 sec. However, these fluctuations were relatively small and likely not biologically meaningful (SD: 0.06 mg/L). A similar event occurred when a powerboat circled the ASV, causing water disturbances from wake currents to heavily affect the ASV's heading and yaw, but variability in the DO readings was also small enough to not impact biological interpretations (SD: 0.01 mg/L; data not shown). However, high variability in sonde readings for future deployments may be a useful indicator of potential sensitivity to robot behavior.

In other situations, sensor data reliability was more prominently impacted by *unintentional interactions* with the environment. For example, the ROV hit the bottom of the lake and stirred up sediment (Fig. 5). This led to misleading water quality readings, including an increase in turbidity followed by a decrease in DO that was simply a result of the unintentional interaction with the sediment.In this case, it was important to have a turbidity sensor paired with the DO sensor, so the cause of the inadvertent sudden drop in DO could be easily identified. The faster response time of the turbidity sensor compared to the DO sensor could predict incoming reading changes for DO or other water quality measurements.

3.2 Robots vs. fixed buoys: Robotic sampling extends DO vertical coverage

The robot-driven sensors and fixed buoy sensors provided complementary information about Lake Sunapee following ice-out (Fig. 2). Traditionally, the period following ice-out is dangerous for manual grab sampling, as the water is so cold and floating ice can be dangerous to navigate around, while robot sampling avoids these issues. ROV sampling along the Winter Buoy line improved the vertical underwater depth resolution, while the higher-frequency data from Sonde A increased the temporal resolution beyond that of the 10 min recording interval of the fixed buoy. ASV sampling extended the horizontal sampling coverage of the lake surface with higher temporal resolution, which will be discussed in Section 3.3.

ROV and Winter Buoy temperature measurements generally agreed (Fig. 2 (a)). During the first 5 weeks, Sonde A temperatures were slightly cooler than the buoy's, while the last week, May 17, shows the opposite pattern. From April 25 to May 17, the ROV consistently stayed at each depth for approximately 1 min. Yet, on May 17 Sonde A produced more variable readings at most depths, possibly due to the greater difference between surface and bottom temperatures requiring a longer response time for the sensor. A comparison of DO concentrations between Sonde A on the ROV and at the top and bottom of the buoy line were also quite similar (Fig. 2 (b)) – the observed discrepancies are within the measurement error of the PME Mini-DOT ($\pm 5\,\%$ of measurement or $\pm 0.3\,\mathrm{mg/L}$, whichever is larger). The offsets may also be due to drift in the sensor calibrations, since neither type of DO sensor was recalibrated during the course of the study. While differences in sensor response times need to be resolved, ROV with Sonde A *greatly increased the vertical resolution of DO data.* In fact, the higher resolution ROV data revealed the development of an oxygen bulge in the middle of the water column on May 17 (Fig. 2 (b)).

A similar correspondence between sensors was observed between data from the ASV with Sonde B when it paused near the Summer Buoy during each *Black path* coverage (Fig. 6 (a)) for a total of 12 expeditions from May 31 to September 11. Sonde B water *temperatures were strongly positively correlated with buoy temperatures* ($r = 0.97$, $N = 12$, p-value $p < 0.01$), as were DO measurements ($r = 0.9$, $N = 12$, $p < 0.01$).

3.3 Robots vs. grab samples: Robotic sampling captures horizontal patterns of chlorophyll data

ASV deployments improved general coverage area and provided real-time data on spatial heterogeneity in the two lakes (Lake Sunapee, NH and China Lake, ME) we sampled. The lakes strongly differ in trophic status, i.e., a classification of waterbodies based on the biological productivity. Lake Sunapee is oligotrophic with low chlorophyll values and high water clarity, while China Lake has higher chlorophyll and lower clarity and would be classified as meso-eutrophic. Our ASV collected chlorophyll fluorescence readings (RFU) each week at three strategic locations in Lake Sunapee (near the home location and the Summer Buoy in Fig. 6). These readings were positively correlated with lab-based measurements of chlorophyll made from grab samples collected during the ASV sampling at these same locations ($r = 0.47, N = 18, p = 0.05$). Measured concentrations in Lake Sunapee were relatively low ($3 - 5$ µg/L) and are likely near the low end for reliable readings from the chlorophyll sensor. In comparison, measured concentrations in China Lake on October 6 were higher (8.42 µg/L, SD: 0.07 µg/L). Interpolated maps of chlorophyll (in RFU) at both Lake Sunapee and China Lake suggested that the continuous data obtained over a wide spatial area from the ASV provided information about spatial heterogeneity in chlorophyll patterns, particularly in China Lake (Fig. 6 and Fig. 4 (b)).

Different spatial coverage paths performed in a single waterbody (i.e., Lake Sunapee) demonstrated horizontal variability in chlorophyll during short-term deployments (Fig. 6, Table 1). Note that the intended proceeding speed was 0.5 m/s for consistent operation, but the actual proceeding speed may have varied depending on environmental factors (Table 1). Although a cyanobacterial bloom did not occur in Lake Sunapee during the expeditions, the coverage methods can help understand the patterns of phytoplankton distribution. A spatial pattern in chlorophyll fluorescence was more visible from the first path coverage scenario (e.g., the line artifacts in Fig. 6 (a) *Black* path rather than (b) *Blue* path, (c) *Red* path), possibly because that was the first path attempted on this date. Data combined from all paths on the same day may slightly obscure this observation, potentially due to water mixing from the ASV movements. However, mean chlorophyll fluorescence was very similar across all three coverage paths (Table 1). Since all paths had a similar speed, the operator/robot can decide on a path pattern and scale to best sample a region of interest, which could be useful for calculating the sparsity of samples for *complete coverage* or updating real-time models in *adaptive sampling*.

ASV deployments may also enhance understanding of the relationship between daily environmental conditions, such as wind and water currents, and within-lake chlorophyll patterns. The line artifacts perpendicular to the long trajectories of the paths (i.e., Fig. 6 (a) *Black* path) could have been from wind or water currents, which usually follow the SE direction, development of Langmuir circulation (counter-rotating vortices on the water surface aligned with the wind; also referred to as windrows), or from interpolation noise within the small range of chlorophyll values. In addition, at China Lake patterns observed along

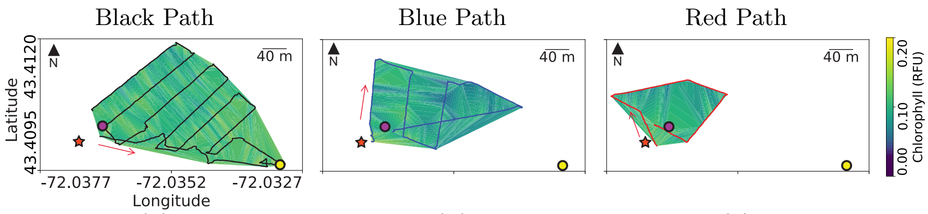


Fig. 6: Three ASV coverage patterns for Lake Sunapee, NH and measurements of surface water chlorophyll fluorescence (RFU, linearly interpolated) on July 15. ***(a)*** *Black path – route to the Summer Buoy and vertical lawnmower.* ***(b)*** *Blue path – diagonal lawnmower.* ***(c)*** *Red path – quadrilateral. Yellow and magenta circles are the Summer and Winter Buoy's locations, respectively. The red star is the home location and the red arrow is the starting direction.*

Region	Path	Area (m^2)	Dist. (m)	Time (sec)	Covg. (m^2/sec)	Speed (m/sec)	Mean Chl (RFU ± SD)	Range Chl (RFU)
Sunapee	Black	47215.22	1921	3016	15.65	0.63	0.11 ± 0.01	0.07 - 0.16
	Blue	24232.06	793	1423	17.03	0.56	0.095 ± 0.02	0.05 - 0.16
	Red	14702.29	530	854	17.21	0.62	0.096 ± 0.02	0.06 - 0.13
China		43267.35	2108	3418	12.66	0.62	0.54 ± 0.05	0.44 - 0.71

Table 1: Lake Sunapee (July 15) and China Lake (October 6) coverage path operation data for the ASV, which includes total area, distance and time traveled, and the area and distance coverage rate. Summary statistics of the chlorophyll fluorescence (RFU) measurements in different scales are also included.

the NE direction (Fig. 4 (b)) could have been from similar environmental effects on the sampling date. The highest chlorophyll concentration occurred in the middle of the coverage area with residual high concentrations in the SW region, so an additional iteration of the coverage path may have shown a movement of the phytoplankton in the NE direction.

4 Discussion and Experimental Insights

Our experiments confirmed that robotic water quality measurements are fairly robust to sensor response times and robotic motions, though there are a few situations that may impact biological interpretations. In particular, varied sensor response times, unintentional robot-environment interactions, and ground truthing need to be considered when designing sampling strategies and in post-sampling data quality control measures. Additionally, future path planning methodologies will improve adaptive sampling to target specific locations and data reliability.

Based on our results to date, we offer the following guidelines for operating robotic water-quality sampling strategies: (1) A robot should stop or reduce speed to provide sufficient time for different sensors to collect accurate readings, especially optical sensors. While speed is commonly recognized as a strategy constraint, we note that multi-directional motions by ROV and horizontal rotation by ASV may impact data quality in some situations. As shown in Fig. 2 and

Fig. 3, response times for sensors in lakes can be different than baseline response times, depending on environmental factors. (2) Allow the robot to self-adjust waiting times for sensor equilibration, similar to adaptive sampling routines; the robot decides when the sensor readings are stable enough to proceed to the next sampling point. (3) The robot should consider factors such as environmental interactions and external forces and minimize their effects when possible. For instance, downward-facing sonar can act as an obstacle avoidance mechanism and help prevent the ROV from stirring up the bottom. For an ASV, studying proper maneuvers can prevent too close approaches from passing boats and counteract leeway caused by wind and currents. Although the ASV did not encounter meaningful instability of the sensor readings during the expeditions, there could be instances where such motions have a significant effect. (4) Robot-collected data should be validated with other data streams when possible, especially when working in new systems so that robot-collected data can be used to scale in both space and time. (5) When robotic movements that may affect sensor reliability can not be avoided, a post-sampling data quality control protocol should be developed specific to the robot instrumentation and environmental conditions. To achieve the future possibility of robots collecting data over larger areas than the traditional limnological sampling that occurs at a few widely separated static places, the robot should plan a path considering (1)-(5), regardless of robotic approaches aimed at *complete coverage* or *adaptive sampling*.

5 Conclusion

The results show that ROV and ASV sampling, when performed with robust validation and quality assurance/quality control measures, can lead to the collection of high quality, spatially and temporally resolved, water quality data. These data are necessary for characterization of whole-lake water quality, identification of hot spots of concern, and ultimately, for prediction of water quality.

Our next step is to conduct extensive tests on different ASV coverage paths (Fig. 6) during a period of decreased water quality, such as a cyanobacterial bloom, to have a thorough understanding of the balance between high resolution of spatial heterogeneity and deployment time. In addition, we will expand our investigation on how to determine, with and without a turbidity sensor, if potential disturbances in the environment cause significant fluctuations in the sonde readings. If such events do affect the reliability of sensors, how should the robot respond? One option, as mentioned in the guidelines, is to let the robot stop and determine when readings are sufficiently stabilized before continuing the path. A more complex solution is to first determine if the location where the unreliable measurements were taken will provide substantial information if resampled, then either send the robot back to resample or let the robot continue on its path, but include adjustments in control to minimize the chance of the event repeating itself.

We aim to extend the system to multiple ROVs and ASVs with a strategic motion planning methodology that is self-aware of sensor characteristics (e.g., response time) and of the impacts from motion attributes (e.g, speed, turning, stopping, collisions). A well-informed system of robots, combined with data collected from existing monitoring efforts, can help create a more holistic picture of spatial and temporal variability within a lake and provide limnologists and lake managers with better data and tools for understanding and predicting changes in water quality, such as cyanobacterial blooms.

Acknowledgment

This work was supported in part by NSF CNS-1919647, OIA-1923004, ICER-1517823, DEB-1753639. We thank the Eliassen family who provided access to sites; the Lake Sunapee Protective Association (LSPA) for boat and buoy assistance; and all the students in the ES 494 Senior Research Capstone class of Fall 2020 in Colby College, in particular, Grace Neumiller, Taryn Waite, and Grace Andrews, for their support in chlorophyll sampling at China Lake, ME.

References

1. Arzamendia, M., Gregor, D., Reina, D.G., Toral, S.L.: An evolutionary approach to constrained path planning of an autonomous surface vehicle for maximizing the covered area of ypacarai lake. Soft Computing **23**, 1723–1734 (2019)
2. Dunbabin, M., Marques, L.: Robots for environmental monitoring: Significant advancements and applications. IEEE Robot. Autom. Mag. **19**(1), 24–39 (2012)
3. Ferri, G., Manzi, A., Fornai, F., Ciuchi, F., Laschi, C.: The hydronet asv, a small-sized autonomous catamaran for real-time monitoring of water quality: From design to missions at sea. IEEE Journal of Oceanic Engineering **40**, 710–726 (2015)
4. Flaspohler, G., Preston, V., Michel, A.P., Girdhar, Y., Roy, N.: Information-guided robotic maximum seek-and-sample in partially observable continuous environments. IEEE Robot. Autom. Lett. **4**(4), 3782–3789 (2019)
5. Fossum, T.O., Fragoso, G.M., Davies, E.J., Ullgren, J.E., Mendes, R., Johnsen, G., Ellingsen, I., Eidsvik, J., Ludvigsen, M., Rajan, K.: Toward adaptive robotic sampling of phytoplankton in the coastal ocean. Science Robotics **4**(27) (2019)
6. Galceran, E., Carreras, M.: A survey on coverage path planning for robotics. Robot. Autom. Syst. **61**(12), 1258–1276 (2013)
7. Garneau, M.E., Posch, T., Hitz, G., Pomerleau, F., Pradalier, C., Siegwart, R., Pernthaler, J.: Short-term displacement of planktothrix rubescens (cyanobacteria) in a pre-alpine lake observed using an autonomous sampling platform. Limnology and Oceanography **58**(5), 1892–1906 (2013)
8. Hitz, G., Galceran, E., Garneau, M.È., Pomerleau, F., Siegwart, R.: Adaptive continuous-space informative path planning for online environmental monitoring. J. Field Robot. **34**(8), 1427–1449 (2017)
9. Hitz, G., Pomerleau, F., Garneau, M.È., Pradalier, C., Posch, T., Pernthaler, J., Siegwart, R.Y.: Autonomous inland water monitoring: Design and application of a surface vessel. IEEE Robotics and Automation Magazine **19**, 62–72 (2012)
10. Jeong, M., Roznere, M., Lensgraf, S., Sniffen, A., Balkcom, D., Quattrini Li, A.: Catabot: Autonomous surface vehicle with an optimized design for environmental monitoring. In: Proc. OCEANS (2020)
11. Karapetyan, N., Moulton, J., Lewis, J.S., Quattrini Li, A., O'Kane, J.M., Rekleitis, I.: Multi-robot dubins coverage with autonomous surface vehicles. In: Proc. ICRA. pp. 2373–2379 (2018)
12. Kraemer, B.: Rethinking discretization to advance limnology amid the ongoing information explosion. Water Research **178** (2020)

13. Teece, M.A.: An inexpensive remotely operated vehicle for underwater studies. Limnology and Oceanography: Methods **7**(3), 206–215 (2009)
14. Welschmeyer, N.A.: Fluorometric analysis of chlorophyll-a in the presence of chlorophyll-b and pheopigments. Limnology and Oceanography **39**, 1985–1992 (1994)
15. Wilkinson, A., Hondzo, M., Guala, M.: Vertical heterogeneities of cyanobacteria and microcystin concentrations in lakes using a seasonal in situ monitoring station. Global Ecol. Conserv. **21**, e00838 (2020)