Use of an Autonomous Surface Vehicle to Collect High Spatial Resolution Water Quality Data at Lake Wateree, SC

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Abstract. Freshwater resources including lakes and reservoirs are increasingly threatened by harmful cyanobacterial blooms (HCBs). The scarcity of high spatial and temporal resolution data presents challenges for monitoring, predicting, and managing these blooms. Autonomous surface vehicles (ASVs) equipped with water quality sensors represent a powerful tool to obtain high-resolution spatial data at Lake Wateree (LW), South Carolina (SC). LW is a hydroelectric reservoir commonly covered with extensive blooms of the benthic cyanobacteria *Microseira (Lyngbya) wollei* and *Phormium sp.*, with the thickest mats in shallow coves.

The main objective of this study was to determine the best speed and duration of loiter (i.e., pauses) required to collect accurate quantitative data on a mobile platform. We present a low-cost motorized kayak (<8000 USD) designed to run autonomously equipped with a YSI EXO2 sonde measuring depth, temperature, conductivity, dissolved oxygen, pH, turbidity, and phycocyanin. The sonde was positioned horizontally on a rigid mount at 0.5 m below the surface to efficiently reduce the effect of turbulence. The data were compared to another YSI EXO2 sonde installed on the same ASV design, maintained stationary midway along the moving ASV's path to assess the data accuracy obtained at different speeds and loiter periods. No statistically significant differences were observed for measurements collected on the stationary and moving ASVs for all water-quality sensors at a speed of up to 2.7 m/s (6 mph). Differences observed between the moving and stationary sondes for phycocyanin and turbidity sensors were within the reported factory accuracy at speeds up to 1.8 m/s (4 mph) and outside the expected factory accuracy at higher speed (2.7 m/s), showing the effects of motion and mixing on the collected data. Dissolved oxygen was outside of the reported factory accuracy for all tests. It is recommended to loiter periodically when moving at a faster speed to obtain more accurate data, as the differences between the sondes were alleviated during the loiter period. Overall, our ASV design has the potential to be employed to obtain robust spatial data at LW when deployed at optimal operating conditions.

INTRODUCTION

Harmful cyanobacterial blooms (HCBs) are becoming more common with increasing temperatures and storm events, and anthropogenic demand for freshwater (Paerl 2016). HCBs put human, animal, and ecosystem health at risk by releasing toxins, impairing water quality, and reducing biodiversity (Paerl et al. 2016; Wurtsbaugh et al. 2019). The main factors controlling HCB proliferation include the presence of stagnant waters, warm temperatures, high light intensity and duration, and nutrient input (Paerl 2008). New technology and tools to monitor HCBs have been employed in the last decade to better identify controlling factors (Catherine et al. 2013; Wood et al. 2020).

Lake Wateree (LW) is in the Catawba-Wateree River Basin, downstream of Charlotte, North Carolina (NC), and the rapidly growing suburbs in York, SC (Baumann 2020). LW is a hydroelectric reservoir that has been subjected to increased non-point and point source nutrient loading from changing land-use patterns for decades such as increased timber felling and sewage discharges, contributing to increased eutrophication (Tufford et al. 1999, 2012). Over the last decade benthic HCBs of *Microseira (Lyngbya) wollei* and *Phormidium sp.* have increased in frequency at LW, with the potential of releasing lyngbyatoxins and saxitoxins under different nutrient (e.g., dissolved nitrogen) and environmental (e.g., temperature) conditions (Yin et al. 1997; Hudon et al. 2014; Heath et al. 2016; Smith et al. 2019; Aziz et al. 2022). Current monitoring efforts by the SC Department of Health and Environmental Control (DHEC) and the Lake Wateree Association only involve discrete bimonthly sampling, which provides insufficient spatial and temporal data resolution to inform prediction and remediation of blooms.

Autonomous Surface Vehicles (ASVs) offer a potential platform for high resolution spatial data, which is otherwise limited by the lack of satellite coverage and discrete manual sampling (Low et al. 2007; Jeong et al. 2020). ASVs, developed for marine monitoring (Low et al. 2007; Das et al. 2011, 2015; Valada et al. 2013) have been recently adapted for freshwater lakes (Hitz et al. 2014, 2017; Manjanna et al. 2018). Robust data, with a high spatial resolution obtained from ASVs, could allow refinement of numerical models used to predict freshwater HCBs. However, the ASV first needs to be tested to determine best practices (e.g., desirable speed and loiter) to obtain accurate data. HCB types (i.e., planktonic versus benthic) as well as lake size and regime are other important considerations affecting ASV design and data collection. The ASV engine causes turbulence during motion which could potentially affect sensor readings, especially during periods of stratification in surface waters. We present a new relatively low-cost (<8,000 USD) ASV equipped with multiple sensors in LW. Several speeds and loiter periods are considered to inform best practices to obtain accurate water-quality data from an ASV.

METHODS

The ASV (Moulton et al. 2018) (Figure 1) is a Mokai kayak that is fitted with a gas-powered engine (Subaru EX21 engine) and jet drive system capable of propelling up to 2.7 m/s (6 mph). The maximum deployment time is 4 hours, limited by the capacity of the gas tank to run the engine at speeds up to 2.7 m/s. The ASV is outfitted with a Pixhawk (Meier et al. 2011) flight controller and an on-board computer, enabling it to operate autonomously and collect time-stamped, geospatial water quality data. The data is stored in ROS bagfiles (O'Kane 2016). During the experiments, the ASV was programmed to autonomously traverse the pre-determined trajectory (Osborne 2019) (Figure 2).

A YSI EXO2 multiparameter sonde was equipped with a suite of EXO sensors to measure depth, temperature, conductivity (contacting/toroidal), dissolved oxygen (optical),

Figure 1. ASV design used in this study.

pH (membrane), turbidity (optical), and phycocyanin (optical). The sonde was positioned horizontally on a fixed mount, facing backwards at about 0.5 m below the waterline, near the base of the mixed layer (Figure 3), on the side and near the back end of the ASV. The sonde readings were recorded in the rapid mode, every two readings (2-sec intervals). Rapid mode is prescribed by the manufacturer for fast moving deployments. In this mode, the instantaneous sensor reading is internally programmed to filter through data collected during the last 2–30 seconds and records the data as a rolling average. The data that were outside of the internal accuracy tolerance were omitted. The data obtained in this mode were treated as continuous data points for the purpose of this study. The ASV was programmed to travel a 483 m transect (Start: 34.42495N, 80.86427W; End: 34.42092N, 80.86608W) at LW and a second stationary ASV was stationed close to the midpoint, approximately 241 m from either end of the transect (34.42295N, 80.86452W) (Figure 2). Water quality data obtained using three different speeds (0.9 m/s, 1.8 m/s & 2.7 m/s) comprised within the lower (0.9 m/s) and upper (2.7 m/s) speed limits of the ASV and two loiter times (20 & 40 seconds) based on observed response times for the sensors in the laboratory (Table 1) were used to determine best practices using this ASV. During the loiter tests the ASV came to a complete halt at three locations along the transect (start, mid-point, and end of the transect), and traveled at a speed of 2.7 m/s when in motion. The motion model controlling the speed of the kayak initiated the stop before reaching the loiter location, so the inertia carried the kayak to the loiter location. Each speed and loiter test was repeated three times.

Response times were recorded in the laboratory by using test solutions encompassing the range of values typically observed at in-situ conditions at LW for each sensor (Table 1). Each sensor was tested (five times) separately to evaluate response times for the two sondes (i.e., moving and stationary) that were used during the deployment. The response

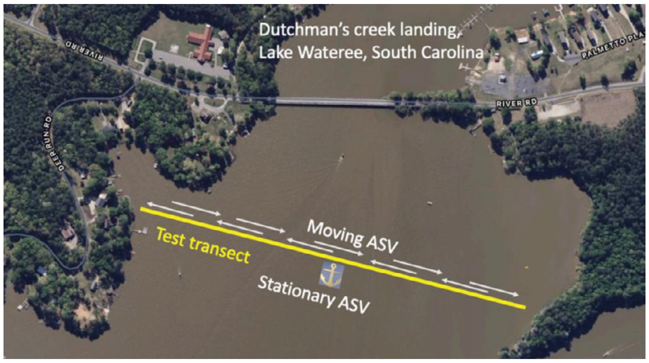

Figure 2. Test transect at Dutchman's Creek Arm of Lake Wateree, SC.

A Shapiro-Wilk test was used to test the normality of data. A paired T-test was used to compare the data between the stationary and moving sondes. The differences between the data recorded using the stationary and moving ASVs during the speed and loiter tests were also compared to the reported manufacturer accuracies (Table 1).

RESULTS

The sensors on the YSI EXO2 (temperature, conductivity, dissolved oxygen, pH, turbidity, and phycocyanin) required a minimum of <1 sec (temperature) and a maximum of 18 seconds (phycocyanin) to read 100% (T100) of the expected test solution value in the laboratory (Table 1). Phycocyanin required the longest time, followed by turbidity, dissolved oxygen, and pH (Table 1). There was a significant difference between T63 and T100 response times (paired T-test; $p<0.05$).

Table 1. YSI EXO2 factory information and laboratory T100 response times for different sensors

Sensor type	Observed variability at LW	Sensor accuracy	Sensor resolution	Factory reported response time (T63)	Laboratory response time (T100)
Temperature	21°C–26°C	-5°C to 35°C: ± 0.01°C 35°C to 50°C: ± 0.05°C	0.001 °C	<1 sec	<1 sec
Conductivity	0.1 mS/cm–0.15mS/cm	0-100 mS/cm: ± 0.5% of reading or 0.001 mS/cm, whichever is greater	0.0001 mS/cm to 0.01 mS/cm	<2 sec	<2 sec
pH	7–10	± 0.1 pH units within ± 10°C of calibration temperature; ± 0.2 pH units for entire temp range	0.01	<3 sec	8 sec ± 2
Dissolved Oxygen	1 mg/L–11 mg/L	0-200%: ± 1% reading or 1% air sat., whichever is greater; 200-500%: ± 5% reading 0-20 mg/L: ± 1% of reading or 0.1 mg/L; 20-50 mg/L: ± 5% reading	0.1% air sat, 0.01 mg/L	<5sec	12 sec ± 3
Phycocyanin	2 RFU–9 RFU	0-100 RFU	0.01 RFU	<2 sec	18 sec ± 4
Turbidity	1 FNU–40 FNU	0-999 ± 0.3 FNU or ± 2% of reading, whichever is greater	0.01 FNU	<2 sec	12 sec ± 3

time, defined as the time it takes for the sonde to stabilize to the expected value (referred here as T100), was noted. The response time was compared to the factory reported response times (T63) which is the response time needed for the sensor to reach 63% of the expected value. The sensors were calibrated the day prior to field tests following YSI EXO2 factory recommendations. The sensors were kept in the same bucket of water to allow comparing values recorded by the two sondes just before the deployment.

Water quality data from the YSI EXO2 sonde mounted on both the moving and stationary ASVs were compared using GPS locations. The data from the moving ASV recorded within 3 m of the stationary ASV for each test was compared.

No significant differences (paired T-test; $p>0.05$) were identified for water quality data collected using the moving and stationary ASVs at all tested speeds and loiter times. Differences between moving and stationary ASVs for conductivity, temperature, and pH sensors were within the expected accuracy at speeds up to 2.7 m/s and loiter time as short as 20 seconds (Figure 4). However, the differences between the moving and stationary sondes were outside the expected

Table 2. Weather conditions at Lake Wateree in October 2022 (CLIMOD2 Station: 388979; Duke Energy).

Date	Maximum Temperature (°C)	Minimum Temperature (°C)	Rainfall (mm)	Lake Depth (m)
04th October, 2022	21.1	6.7	0	29.5
21st October, 2022	18.9	0.6	0	29.3
Average (04th-21st October 2022)	23.9 ± 3.7	8.3 ± 4.5	0	29.5 ± 0.1

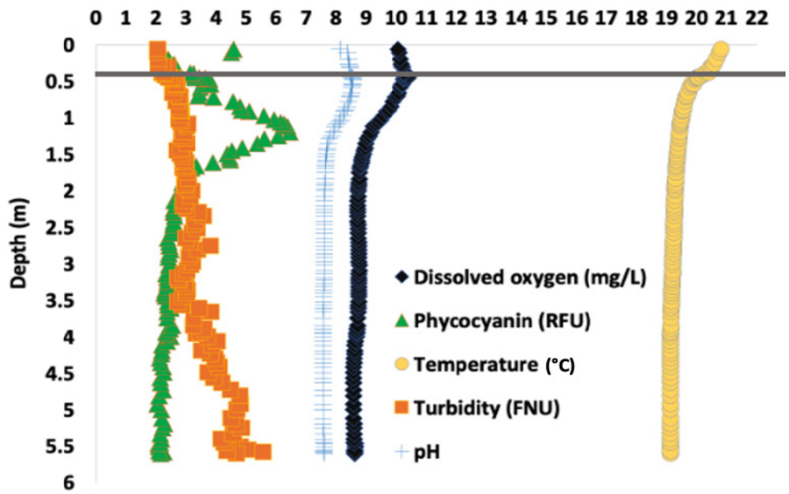

Figure 3. Depth profile of dissolved oxygen, phycocyanin, temperature, turbidity and pH collected at the same location as a stationary sonde on a ASV on October 21, 2022. The horizontal gray line indicates the position of the sonde mounted on the ASV.

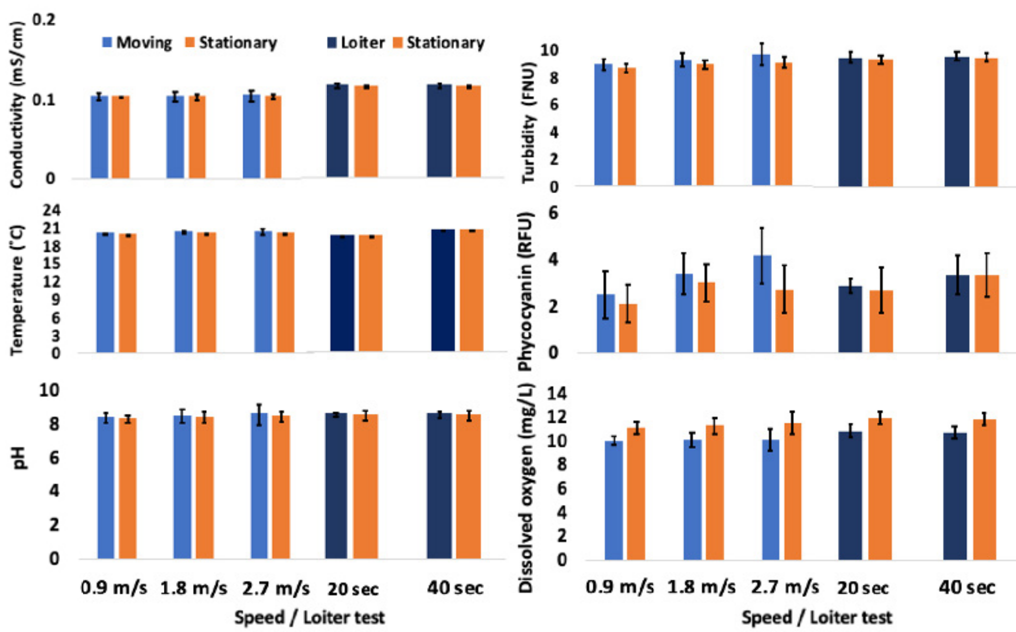

Figure 4. Sensor data plotted as means with standard deviation for different speed and loiter tests at LW for both the moving and stationary sondes. The experiments were done at the same location through the course of the day on October 4, 2022.

accuracy at 2.7 m/s for turbidity and phycocyanin (Figure 4). These sensors also had higher T63 and T100 (Table 1). The difference between the moving and stationary sondes for dissolved oxygen were consistently outside the expected accuracy for all tests (Figure 4, Table 1). The stationary sonde data were considered to be more accurate due to the longer equilibration time with the surrounding water. Vertical profiles collected two weeks after the experiment showed that surface waters were stratified during our test period, with dissolved oxygen maximum around 0.5 m depth and variable phycocyanin within the first two meters of the water column (Figure 3). A change in the stratification between these two sampling times is unlikely since weather conditions in October were relatively stable (Table 2; also see Lewis et al. 2011).

DISCUSSION

We present a new, relatively low-cost (<8,000 USD) ASV that can be used to collect high quality spatio-temporal data at LW at speeds up to 1.8 m/s. These results corroborate previous use of similar ASV designs, mainly in coastal marine environments, used to obtain high spatial resolution data to monitor HCBs (Leong et al, 2012; Beckler et al. 2019).

Our data (Figure 4) showed that turbidity, phycocyanin, and dissolved oxygen readings are affected by motion (i.e., turbulence), especially at a speed of 2.7 m/s. Notably, dissolved oxygen measurements from the stationary sonde were 1.2 ± 0.4 mg/L higher than the moving sonde at all tested speeds. These differences are much higher than the factory reported accuracy of the oxygen sensor (Table 1). This discrepancy was not due to drift because the difference between readings of the two sondes were within 0.3 mg/L at the start of the tests. We posit that the lower oxygen values from the moving sonde were likely due to greater mixing with waters above or below the oxygen maximum around 0.5 m depth, for the moving sonde (Figure 3). Another possibility for observing dissolved oxygen readings outside the manufacturer reported accuracy is sensor malfunction. However, no evidence for malfunction was observed as the sondes were thoroughly tested before the experiment. In addition, response time may be longer than 40 seconds under field conditions. Mixing could also explain the difference observed at a speed of 2.7 m/s for the phycocyanin sensor as this parameter was also highly variable within the first meter of the water column (Figure 3). Motion is also expected to similarly affect turbidity measurements as it is based on scattering of light in the water (Merten et al. 2014).

Although there were no significant differences (paired T-test; p>0.05) between the data from the stationary sonde and moving sonde at all speeds and loiter times, we recommend to carefully evaluate the optimal speed for ASVs equipped with water quality sensors based on the manufacturer reported accuracies for the different sensors (Table 1) to minimize the effects of motion. Our results showed that 1.8 m/s was the preferred speed to obtain reliable data at LW for our ASV based on the manufacturer expected sensor accuracy. Further, the observed deviation from the expected accuracy between the moving and stationary sondes for the turbidity and phycocyanin sensors were alleviated during loiter periods. We thus recommend periodic loiters of at least 20 seconds to obtain more accurate data, especially for sensors with longer response times and during stratified conditions. Discrete sampling should be used to evaluate the frequency of loitering based on the level and depth of stratification and spatial heterogeneity of the surface waters and to validate the data collected by the ASV.

Overall, this study demonstrated the potential to use water-quality sensors on ASV in freshwater environments. Future work will involve using this ASV along a trajectory path around LW (Salman et al. 2022) which delineates the shore since benthic HCBs, that are only present in shallow waters, are the focus of interest. We plan to loiter every 500 m for 20 seconds at 1.8 m/s and cover 24 kms (7% of the shoreline) in approximately 4 hours. This should enable time-effective large spatial coverage to capture minute spatial heterogeneity in water quality at LW.

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