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Interactive monitoring in reservoirs using NUSwan – preliminary field results

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Abstract

Water quality monitoring of large freshwater bodies is usually slow and laborious, resulting in very sparse samples. This paper presents the design and preliminary field results from a network of low-cost mobile robots called NUSwan, a system aimed at addressing this issue. NUSwan robots can autonomously traverse a reservoir to provide real-time water quality data over the Internet, and allow users to modify the sampling missions interactively based on their interpretation of the data. The quality of measurements generated is comparable to that obtained from standard manual sampling. Moreover, the system incurs little logistics overhead while allowing higher monitoring frequency and spatial coverage. We present an example to show NUSwan's capability in detecting the emergence of water quality hotspots. Lastly, we demonstrate the potential of using data collected from a short mission carried out by NUSwan to rapidly assess the relationship between water quality indicators.

Key words: cloud, environmental monitoring, environmental robotics, interactive, water sampler, spatiotemporal

INTRODUCTION

Freshwater environments can be complex and highly dynamic, with physical properties that fluctuate substantially over space and time. To better understand, monitor, and manage the water resources, researchers are required to measure the water quality parameters regularly at diverse locations over different periods (Atkinson & Mabe 2006; Carraro *et al.* 2012; Zhang *et al.* 2015). Long term site studies (Akyuz *et al.* 2014; Su *et al.* 2015; Wang *et al.* 2015; Yan *et al.* 2016) and satellite imagery (Nellis *et al.* 1998; Bergamino *et al.* 2010; Pu *et al.* 2017) have shown evidence of spatiotemporal dynamics in water quality variables in lake environments. Human activities (Warnken & Buckley 2004; Krogh *et al.* 2009), urbanisation and land use (Ahearn *et al.* 2005; Almeida *et al.* 2007; Zhao *et al.* 2013; Kändler *et al.* 2017) have been reported to affect water quality in catchments and rivers. Consequentially, the increase in recreational activities and urbanization around reservoirs adds complexity to water body system with more diverse contamination injections over space and time. Furthermore, boating activities introduce additional perturbations to the existing natural mixing processes including resuspension of bed sediments (Pettibone *et al.* 1996) in the water body. These lead to the increase in physical and biological interactions, causing complex

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environmental events such as algae bloom and changes in water quality that are sparse and localized to occur more commonly. An improved data collection frequency is needed to maximize the chances of detecting these scattered events and potentially identify and locate the source. To both researchers and water body management agencies, the challenge is to achieve this efficiently with limited resources available.

Typical methods of reservoir monitoring include the use of automated fixed stations at a few selected locations, periodic but slow manual measurements at some additional locations to supplement the observations at the fixed stations, and occasional deployment of robotics systems such as Autonomous Underwater Vehicle (AUV) and Unmanned Surface Vehicle (USV) for spatiotemporal observation. Fixed stations are capable of providing high-resolution temporal data in real-time, but they lack mobility. Although AUV and USV are competent in supporting general spatiotemporal surveys (Ellison & Slocum 2008; Dunbabin *et al.* 2009; Brown *et al.* 2011; Koay *et al.* 2011; Ng *et al.* 2015), they tend to be too expensive and logistically demanding to be used for daily operations. Hence, their deployment for water quality measurements are typically focused on ad-hoc studies that involve conducting multiple survey trips over carefully selected time intervals and locations (Ishikawa *et al.* 2005; Zhang & Sukhatme 2007; Hemond *et al.* 2008).

This paper presents preliminary trial results, and a description of the New Smart Water Assessment Network (NUSwan), a robotic platform designed to provide unattended spatiotemporal water quality monitoring in reservoirs. The NUSwan is a network of low-cost mobile robots that can autonomously survey a water body, providing real-time water quality measurements over the Internet, and at the same time allowing its users to modify the missions interactively. It also permits users to collect 1-litre water samples at locations of their choice, typically decided based on observations of real-time data. Lastly, the robot is creatively designed in the guise of a white swan swimming peacefully in the reservoir as it carries out its missions. The system has been tested as part of daily reservoir operations to assess its potential in increasing the measurement frequency and spatial coverage of freshwater monitoring.

METHODS

The system architecture of NUSwan consists of three main components: a command center, a fleet of autonomous robots, and a home-station that the robots return to (Figure 1). All the robots are connected to a central server through cellular connections, allowing near real-time data distribution and mission control. Typical daily operations start with the deployment of multiple robots from a dock in the morning; they will then autonomously sample the field and return to the dock at the end of the day for recovery and charging. The system is designed to separate data user from field operations while allowing synergy between them. All the data communication links between the robots, the server, and the users are encrypted through standard Secure Socket Layer (SSL) for data security (Weaver 2006). The following sections describe the system in detail.

An efficient operational paradigm

The operational design of NUSwan segregates operations between the operation teams, maintenance team, and data users to achieve efficient manpower usage and optimum system utilization. The operational paradigm provides the necessary level of coordination among the groups to allow them to function without the need for a tight coupling between them, as illustrated in Figure 2. Data users are the group of users that control the collection, holding, processing, and the use of data from NUSwan. They typically are the environmental scientists, modelers, reservoir managers, or other

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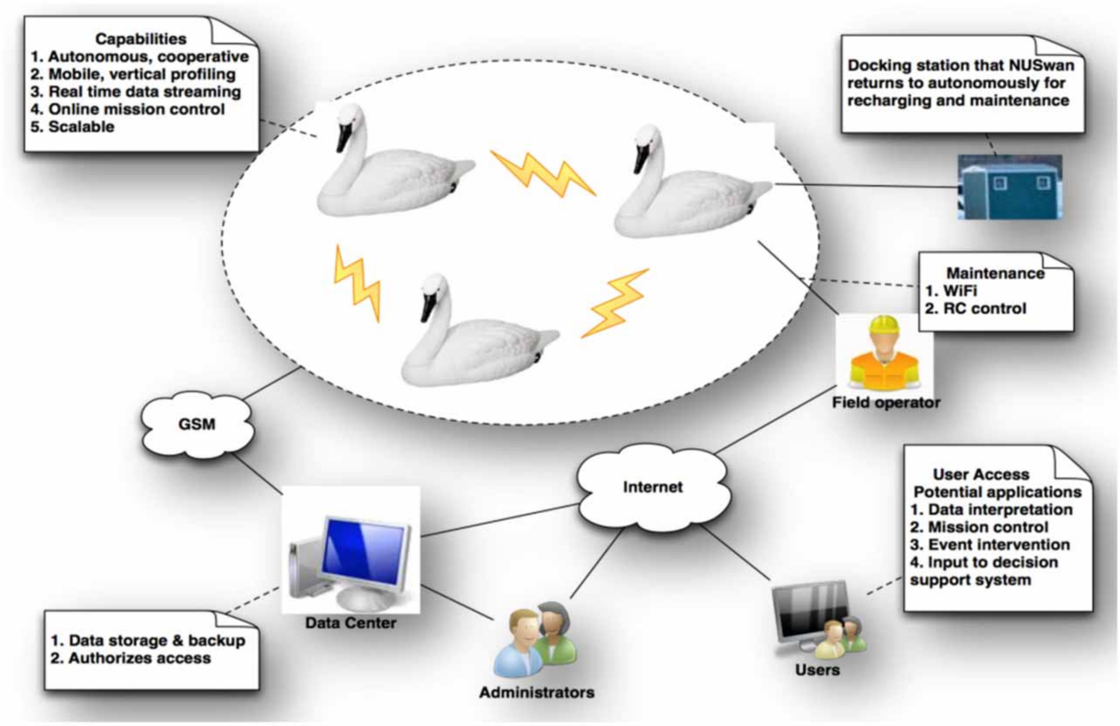

Figure 1 | System architecture of NUSwan.

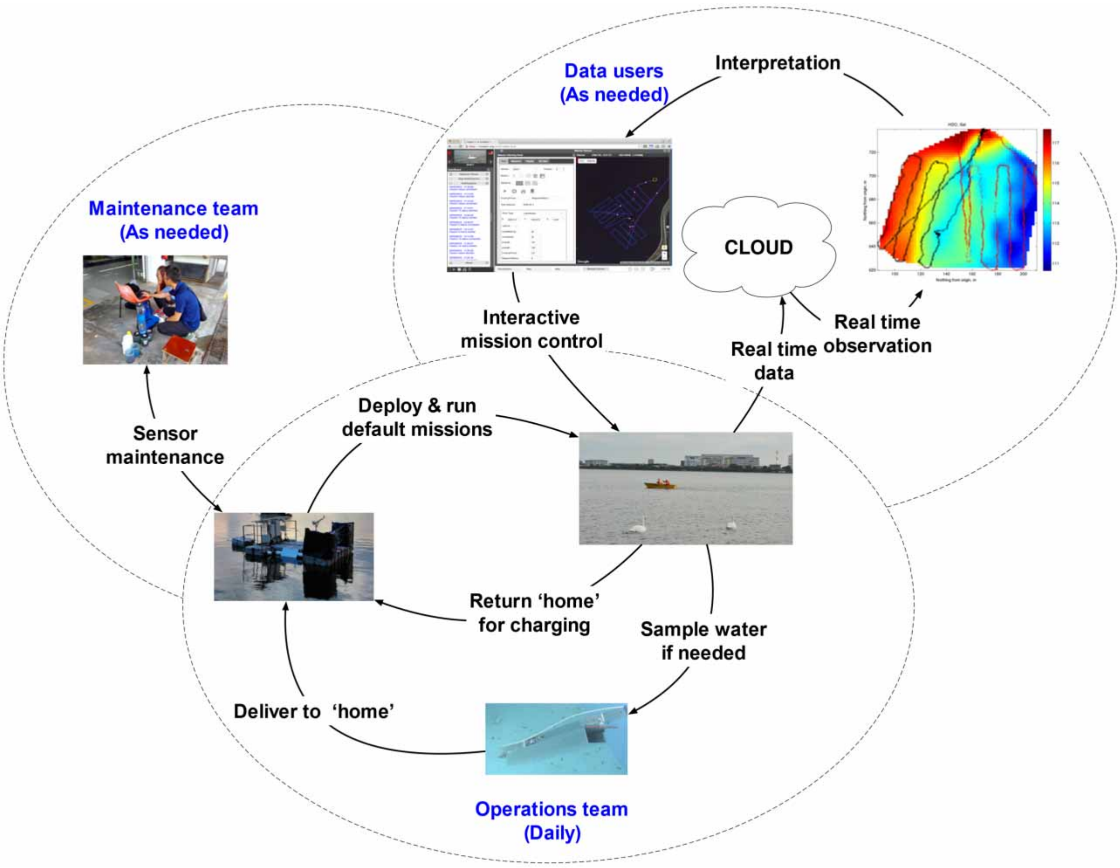

Figure 2 | Operational architecture of NUSwan. The three bubbles represent the flow of different operational roles in the system. Users domain represents the data consumers who can interpret the data and decide new sampling strategies in real-time as needed. Operations team supports the daily operations while maintenance team ensures proper sensor calibrations and minimize system downtime.

stakeholders that interpret the data and alter the missions of the robots without having to be involved in field operations.

The operations team provides daily field support for NUSwan robots using only mobile phones and simple radio control units. Usually, the operations team is also the operation unit of the particular reservoir that NUSwan is deployed in. The team needs to spend only a fraction of the work hours to deploy, recover, and charge the robots, as well as collect water samples for analysis whenever the NUSwan collects water. After deploying the robots, the operations team relinquish control by sending the robots to their default missions or have them lingering at designated positions. Data users then take over the control of the robots or let them continue with their routine missions. The NUSwan sends notifications to the operations team whenever any of the robots requires physical attention or needs recovery. Such a loosely coupled operation mode frees up the operations team to support other tasks in the reservoir, making the system very suitable for daily deployment.

Lastly, the maintenance team consists of engineers that focus on maintaining the robotic platform and calibration of the sensors at regular intervals. This provides a clear delineation of roles and allows each group to operate efficiently in their area of competency.

NUSwan robots and their homes

For simplicity of operation and cost effectiveness, the NUSwan robot is designed as a minimally propelled autonomous surface craft that performs short profiling at locations of interest. Since the robot spends its time on the surface, it avoids the need for expensive sensors or complicated setup of acoustic beacons required to track submerged vehicles, and uses simple Global Positioning Systems (GPS) technology for its navigation. To measure water parameters below the surface, NUSwan carries a robotic arm capable of extending below the water surface up to 1.5 m. Unlike typical AUVs and USVs that use significant propulsion energy to accurately follow mission paths, NUSwan traverses a set of mission points along a nominal path to save on power consumption. This minimizes the size and number of batteries, keeping the robot small and light; hence allowing for easy deployment, recovery, and transportation of the robot by a single person.

The robot minimizes operational logistics by autonomously returning to a predefined home location near the shore for regular maintenance and charging. The return can either be preprogrammed in the missions or triggered through Short Message Service (SMS) from a standard mobile phone or a web browser. The home location can simply be a point near a pier for the robots to rendezvous with operators, or a customized solar station to charge the robots where the power grid is not available.

As the name suggests, the NUSwan robots are in the guise of white swans to blend into the natural environment of reservoirs. Each of the robots carries a unit of a commercially available multi-parameter probe and a miniature one-liter water sampler attached to its extendable arm located under its belly. The sensor suite can be easily upgraded to provide new parameters by swapping or adding compatible probes with negligible software changes, typically involving modifications of some configuration files. Other non-compatible sensors can also be added with minimal effort thanks to the modular software (Chitre 2008) and hardware architecture that allow quick reconfigurations of the system. Figure 3 shows the NUSwan robots, and a customized home-station constructed in a reservoir. Table 1 summarizes the specification of the robots.

The NUSwan's command and control implementation is based on a flexible robotic framework (Chitre 2008; Tan & Chitre 2012) developed for STARFISH AUV (Koay *et al.* 2011). It provides an efficient platform to develop new robotic behaviors easily without having to worry about low-level controls and used in to support various robotic studies (Gao & Chitre 2010; Tan *et al.* 2014, 2015). These robotic behaviors form the various 'tasks' that users can use to plan missions for their environmental sensing needs. A typical mission consists of a combination of tasks such as 'measure water quality at a given location and depth over a period'; 'map an area with lawnmower maneuver

Figure 3 | A customized home-station where NUSwan robots return to, and charge using energy harnessed from solar panels (left). NUSwans executing autonomous missions in a local reservoir in Singapore (right).

Table 1 | NUSwan vehicle specifications

Descriptions		Remarks
Dimensions	100 cm × 80 cm × 60 cm	With mechanical arm folded
Weight (air)	12 kg	–
Battery	270 Wh	Rechargeable lithium-polymer
Endurance	9–16 hours	Mission and battery configuration dependent
Maximum speed	2 knots	Straight run with no external disturbance
Control	Differential drive	Using in-house propulsion motors
Communications	GSM, WiFi, RF	Daily data and mission telemetry via 2–3G network
		RC control, SMS, and WiFi for maintenance
Navigation	GPS	
Typical data rate		0.5 Hz internal logging and 0.2 Hz server logging. This is user configurable.
Sensors	Water parameters	Chlorophyll-a fluorescence, specific conductivity, depth, temperature, DO, turbidity, blue-green algae fluorescence, pH, ORP
	Water sampler	1 L
	Image	240 × 320 pixels, every 10 sec
	General	All data is time-stamped and geo-tagged
Probe depth	0.2–1.5 ± 0.1 m	Programmable in mission

coverage'; 'grab one liter water sample at a given place and depth'; 'visit a particular location'; and 'loiter at a location for a period of time'. The operational capability of NUSwan can be easily extended with new robotic intelligence through the same framework. Some key improvements planned include adaptive sampling, plume tracking, multi-vehicle cooperative sensing and so on.

Interactive mission control and planning

A clean and lean browser-based graphical user interface was developed to provide a tool to manage users, robots, as well as the data and the mission. It allows data users to observe the field and alter the measurement behavior of the robot from any location with Internet connectivity. Data users can also

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set thresholds on any sensor data so that the server will send SMS and/or email alerts to stakeholders when triggered. This alert mechanism provides the capability of event-based operations. NUSwan robots carry out routine monitoring missions, and upon being triggered, alert users to critical events for their investigations. Users can observe the status of the robots and the evolution of spatial data, re-plan the missions accordingly and execute them.

RESULTS AND DISCUSSION

The NUSwan system was test-bedded for more than six months to assess its operational capability, the quality of data collected, and the practicality of the operational paradigm in reservoir operations. The system has been deployed in two reservoirs with active recreational activities and challenging environments. The following sections present some of the important findings.

Operational integrity

The test results show good coherence between the teams based on the operational paradigm described in Figure 2. During the test-bedding period, data users issued operational requests to the operations team through a standard social chat application on their mobile phones. The requests were categorized into high and low priority tasks. The operations team was required to respond immediately to high priority tasks while low priority tasks could be attended to at a later time. Low priority requests dealt with robot deployment and recovery while high priority requests included retrieval of water samples collected by NUSwan.

Daily communication records were collected and analyzed to understand the day-to-day operating overhead incurred during the test-bedding, as shown in Table 2. Response time is the time elapsed from the moment the task is requested to the end of the task execution. Actual effort is the amount of time the operations team spent to work on the task. Results show that low and high priority requests were typically fulfilled within 30 and 13 minutes respectively while the typical effort to deploy or recover the robots took only 15 minutes.

Table 2 | Typical effort expended by the operations team and the response time to each type of requests during the test-bedding period

	Response time Median (min)	Effort Median (min)
High priority requests	13	–
Low priority requests	30	15
Time to recover/deploy robots	–	15

Comparing data consistency between NUSwan robots

NUSwan robots use commercially available probes to measure the water quality parameters. The choice of sensors naturally limits measurement accuracy. We are interested in quantifying any inconsistency in measurements due to robot dynamics. Two units of NUSwan robots were deployed loitering within 15 m of each other for a day. We compared more than 5,700 pairs of time-synchronized water parameter measurements collected by the robots. The results show that the precisions of readings of chlorophyll-a fluorescence (Chl-a), dissolved oxygen (DO), pH, specific conductivity, temperature, and depth between the robots were within expectation given the accuracies of the probes, see Figure 4. The deviations in turbidity readings exhibited a larger spread than anticipated; a close examination of the data shows that there were spikes in individual sensor measurements.

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Since the measurements were made near the surface of the water with relatively low turbidity while the vehicles were in motions, the fluctuations could be attributed to the effect of bubble formation. Further studies are needed to confirm the hypothesis. Once the cause of the fluctuations is found and proven, robotic intelligence can be added to handle the required measurement behavior.

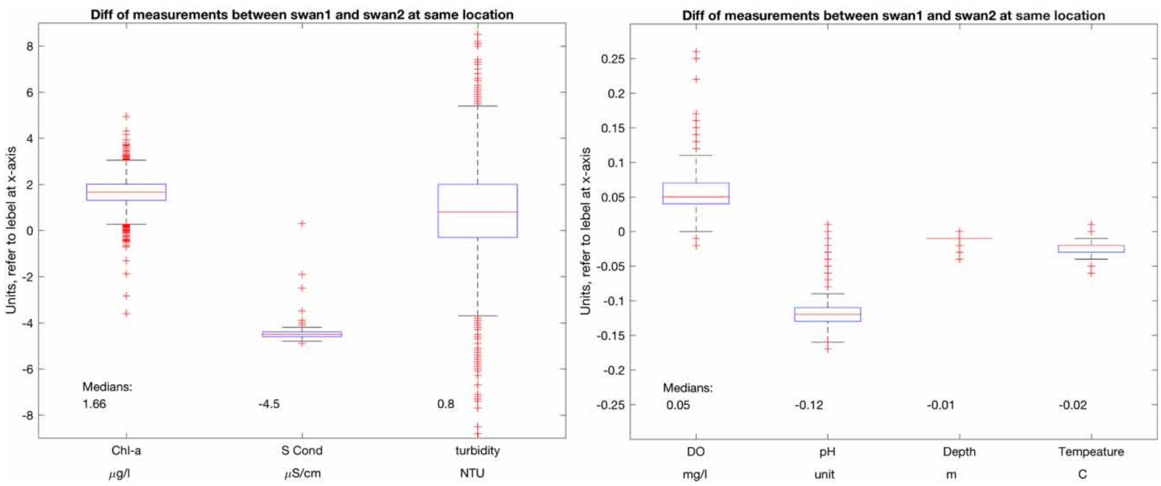

Figure 4 | Boxplots of the deviations of the readings between two NUSwans located close in proximity. The boxes represent interquartile range (IQR) of 25th-75th percentile, the red band represents the median. The whiskers represent the upper and lower 1.5 IQR of the deviations covering 97–98% of all measurements. The anticipated variations between the probes based on their tolerances are: ±2.12 µg/l (Chl-a), ±6.36 µS/cm (specific conductivity), ±0.16 NTU (turbidity), ±0.08 mg/l (DO), ±0.28 (pH), ±0.04 m (depth), and ±0.14 °C (temperature).

Comparing measurements between NUSwan and manual sampling in the field

A set of experiments was conducted to compare the measurements taken by NUSwan with those taken manually. These include comparisons of measurements between in-situ sensors, between in-situ sensors and laboratory analysis of actual water samples, as well as between laboratory analysis of water samples collected by both methods.

Comparing NUSwan readings with physical samples

A total of 24 samples were taken in this experiment and sent to an accredited laboratory for analysis of pH and conductivity. Fifteen of them were taken manually along with the robots while they were underway, six while they were stationary while the robot's auto-sampler took the remaining three. Nineteen water samples were used to compare with the measurements from the robot's in-situ sensors while three pairs of water samples were used to compare the performance of manual sampler against the NUSwan sampler. The differences in their measurements are summarized in Table 3.

The result shows that the measurements from water samples taken by the robots were consistent with those taken manually. The in-situ readings of pH taken by the robots were also consistent

Table 3 | Comparisons between laboratory analysis results of manually sampled water, NUSwan sampled water and NUSwan in-situ sensor

	Laboratory analysis		Differences (r.m.s)	
Parameters, units	Analysis methods	Manual (mean)	In-situ	Sampled water
S. Conductivity, µS/cm	APHA Pt 2510B	367	28.1	2.3
pH	APHA Pt 4500-H + (B)	8.8	0.1	0.2

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with laboratory analysis. However, the deviation between in-situ readings and laboratory analysis results of specific conductivity was three times more than expected. As both probe-to-probe (see the following section) and laboratory-to-laboratory analysis only shows minimal differences, environment factors during the measurements and differences in measurement methodologies may have contributed to the larger than expected variation.

Comparing NUSwan in-situ readings with readings from a handheld probe

A total of 16 measurements were taken using a handheld probe, suspended from a boat 0.2–0.5 m below the water surface and within 10 m from the positions of the NUSwan robot. Nine measurements were taken in a static condition when both the NUSwan and the boat ceased their propulsions and were drifting under the influence of the same surface wind. The boat waiting ahead of the robot's path took the remaining measurements at the instant the robot drew near.

Table 4 summarizes the differences between the measurements observed. The measurements taken with the robot in motion are comparable to the tolerance of the probe, except DO. Considering that the comparison was made with a small number of readings taken in dynamic conditions using different types of sensors, this is expected. A surprising observation is that deviations of measurements under static conditions have larger offsets and spread as compared to the measurements taken in dynamic conditions, except pH. As the static measurements were made near a jetty in operation, the deviations may be attributed to site conditions and environment factors such as the presence of aeration equipment, pumps, boat movements, etc.

Table 4 | Differences between measurements from a handheld probe in static and NUSwan in-situ probe both in static and mobile

			Differences			
			Static		Mobile	
Parameters, units	Probe accuracy	Handheld readings mean	mean	std	mean	std
Temperature, °C	± 0.15	30.8	−0.65	0.15	−0.19	0.25
Specific conductivity, μS/cm	1% ± 1	389	−1.64	0.61	−0.70	0.47
DO, mg/l	± 0.2	8.1	−0.27	0.60	−0.03	0.63
pH	± 0.2	8.0	−0.36	0.20	−0.61	0.08

Spatiotemporal mapping of water parameters

Apart from the ability to remotely collect environmental data at desired locations and periods, NUSwan robots were also tested for their spatiotemporal mapping capability. This ability is useful in capturing localized, transient environmental events that are often misrepresented or missed by fixed-stations sampling or manual sampling.

Observing the emergence of localized hotspots

Two robots were deployed in the same area to cross-check on each other's spatial mapping of potential events. Figure 5 shows an emerging hotspot event captured by two consecutive lawnmower surveys by one of the robots. The commercial probes used in the robots provide Chlorophyll-a fluorescence level readings that need further calibrations to reflect the absolute Chlorophyll-a levels on the ground. To avoid confusions, the spatial distributions of Chlorophyll-a fluorescence are presented as a

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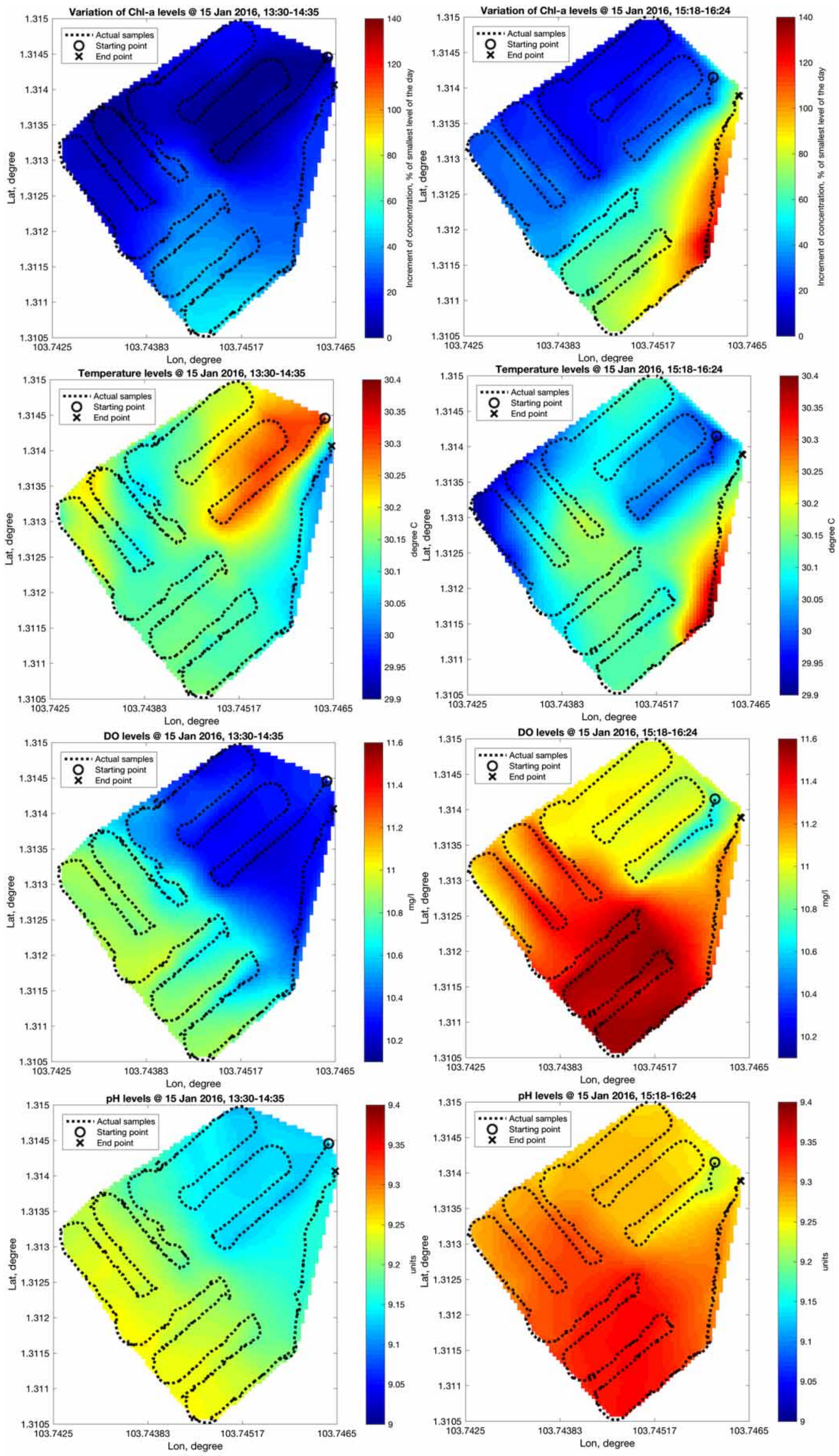

Figure 5 | An emerging hotspot measured by NUSwan robot after a repeat in mappings over the same area. The plots are 2-D data generated using natural neighbourhood interpolation from actual measurements (marked by dots) collected. The x and y-axes point to east and north respectively. The first mission measured lower Chl-a fluorescence, DO, and pH levels (plots in the left column) while the second visit showed increased readings in certain parts of the area (plots in the right column).

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percentage of intensity increment with reference to its lowest level in both the runs (Figure 5, top row) while the remaining parameters are presented in their standard units.

Each lawnmower path covered an area of nearly 0.16 km^2. It took slightly more than an hour to complete, during which the field was assumed to be pseudo-static. The emergences of hotspots were observed about 0.2–0.3 m below the water surface across a period of slightly more than 3 hours. The second robot that took an approximately orthogonal lawnmower path in the same area had also observed the same event at the time (not shown here), confirming its existence.

The snapshots of the spatial mapping showed an increased pH and DO concentrations in the south-western region, which also elevated the concentrations to the east as time progressed (Figure 5, third and fourth rows). At the same time, a warm patch of water appeared to move from the north-eastern region towards south (Figure 5, second row). Along with these observations, a localized increase in Chlorophyll-a fluorescence readings emerged in the south-eastern region. The availability of snapshots of spatial variations over time provides rich information for an expert in the field to interpret the cause of the observed phenomena. A robot that can adaptively detect and follow the hotspots may further reveal details of the dynamics. We are currently exploring further development in this direction.

Studying the relationship between water parameters and temporal events

The historical spatiotemporal data gathered by the NUSwan could provide valuable information needed to understand the relationship between water parameters and environmental observations. Dataset from a single mission could be sufficient to uncover such relationships if they cover a hotspot. The second mission shown in Figure 5 is a good example. The mission took about 80 minutes to cover an area of 0.15 km^2 and generated more than 1,000 data points with different concentration levels. A nonparametric measure of statistical dependence between Chlorophyll-a fluorescence and other water parameter readings was calculated to study their relationship, as summarized in Table 5.

Table 5 | Correlation between Chlorophyll-a fluorescence intensity and other water parameters estimated from a single 80-minute mission

Parameters	ρ	p-value
DO	0.624	0.00
pH	0.589	0.00
Temperature	0.478	0.00
Turbidity	0.490	0.00
Specific conductivity	0.409	0.00

Their relationship is shown by the Spearman's correlation coefficient, ρ, where ± 1 indicates that both parameters are perfect monotone with each another. The p-value shows the statistical significance of the observations, where a value smaller than 0.05 indicates the observation is unlikely to arise from randomness.

Coupled with the threshold notification and ability to alter missions on the fly, NUSwan provides a powerful tool for stakeholders to detect and sample localized events and to understand them better.

CONCLUSIONS

We presented a new water assessment robotic platform, NUSwan, along with its preliminary field results. NUSwan has been extensively tested in the field under realistic reservoir operating conditions and has demonstrated its potential to function as one of the daily reservoir operations. The robotic platform produced measurements with comparable accuracy to existing manual methods. More importantly, it provides near-persistent spatiotemporal monitoring in real-time while allowing users

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to alter sampling missions remotely. This significantly increases the chances of capturing and studying spikes and hotspots of water parameters in highly dynamic environments that would otherwise be overlooked.

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