

Autonomous Greenhouse Gas Sampling Using Multiple Robotic Boats

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Abstract Accurately quantifying total greenhouse gas emissions (e.g. methane) from natural systems such as lakes, reservoirs and wetlands requires the spatial-temporal measurement of both diffusive and ebullitive (bubbling) emissions. Traditional, manual, measurement techniques provide only limited localised assessment of methane flux, often introducing significant errors when extrapolated to the *whole-of-system*. In this paper, we directly address these current sampling limitations and present a novel multiple robotic boat system configured to measure the spatiotemporal release of methane to atmosphere across inland waterways. The system, consisting of multiple networked Autonomous Surface Vehicles (ASVs) and capable of persistent operation, enables scientists to remotely evaluate the performance of sampling and modelling algorithms for real-world process quantification over extended periods of time. This paper provides an overview of the multi-robot sampling system including the vehicle and gas sampling unit design. Experimental results are shown demonstrating the system's ability to autonomously navigate and implement an exploratory sampling algorithm to measure methane emissions on two inland reservoirs.

1 Introduction

Quantification of greenhouse gas emissions to atmosphere is becoming an increasingly important requirement for scientists and managers to understand their total carbon footprint. Methane in particular is a powerful greenhouse gas, approximately 21 times higher global warming potential than carbon dioxide. Water storages are known emitters of methane to atmosphere [11]. The spatiotemporal variation of release is dependent on many environmental and biogeochemical parameters. Therefore, in order to accurately quantify this greenhouse gas release requires long duration and repeat monitoring of the entire water body.

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There are two primary pathways for methane to be released from water storages; (1) diffusion, and (2) ebullition (or bubbling). Diffusion is the most common pathway considered due to greater consistency across a waterway. Rates of methane ebullition represent a notoriously difficult emission pathway to quantify with highly variable spatial and temporal changes [6]. However, the importance of bubbling fluxes in terms of total emissions is increasingly recognised from a number of different globally relevant natural systems including lakes, reservoirs and wetlands. This represents a critical challenge to current manual survey efforts to quantify spatiotemporal greenhouse gas emissions and reduce the uncertainty associated with bubbling fluxes. This is where robotics can play a significant role.

In this work, a novel system for direct measurement of the combined diffusive and ebullitive methane flux and an ability to persistently monitor a wide spatial area is presented. Named the *Inference* Robotic Adaptive Sampling System, it consists of multiple (four) networked robotic boats (see Fig. 1) and provides an open architecture allowing researchers to evaluate new sampling algorithms with customisable scientific payloads on real-world processes over extended periods of time.

The contributions presented in this paper are; (1) A novel ASV system for navigating complex inland waterways, (2) a new greenhouse gas sampling system, (3) a multi-robot sampling strategy to survey a previously unseen environment, and (4) an experimental evaluation of the entire system on two inland water storages.

The remainder of this paper is as follows: Sect. 2 provides background information. Section 3 describes the *Inference* system and the gas sampling system. Section 4 describes a preliminary sampling methodology with Sect. 5 showing results from two inland water storages. Finally, Sect. 6 draws conclusions and discusses future research.



Fig. 1 The multi-robot *Inference* Robotic Adaptive Sampling System

2 Related Work

Robotic platforms capable of persistent environmental monitoring offer an efficient alternative to manual or static sensor network sampling for studying large-scale phenomena. However, in practice most applications are short-term experiments for validating existing models [3]. Recent cross-disciplinary research extensively used robots to investigate assumptions around spatiotemporal homogeneity of environmental processes such as toxic algal blooms in lakes [5] and methane production in reservoirs [6]. These studies show that combined robotic persistence and spatiotemporal sampling can provide significant new insight into environmental processes. However, there are challenges to achieving persistent robotic process monitoring, particularly in the complex environments considered here. These primarily relate to robotic platforms for persistent navigation within complex and often dynamic environments, and the ability to adaptively coordinate multiple robots to appropriately sample the process of interest.

Robotic monitoring of marine and aquatic environments has received considerable attention over the last two decades [3]. Whilst most studies have focused on underwater vehicles with restricted payloads and endurance, there is now increasing focus on Autonomous Surface Vehicles (ASVs) with greater endurance and payload carrying capacity for large-scale unsupervised environmental monitoring [12, 13, 16]. These systems are primarily designed for oceanographic surveys and are not particularly suitable for relatively unexplored inland waterways with challenging and often varying navigational requirements.

Recently, a series of ASVs have been designed and applied on inland waterways. Typically, these catamaran style vehicles are of sufficient size for carrying scientific payloads for tasks such as mapping hazards above and below the waterline [4], and water quality monitoring [1, 7]. Whilst demonstrating environmental monitoring capabilities, there is little flexibility for adding external payloads and their navigation capabilities are generally customised to the specific environment. The provision of a flexible, yet capable, robotic platform is a key consideration in this research.

Navigation around narrow inland waterways is often more challenging than for the ocean due to issues such as above, below and on-water obstacles and GPS reliability (e.g. in mountainous and forested systems). A number of sensors have been used to detect obstacles and in identifying free-space paths. Hitz et al. [7] use water depth only for detecting shallow regions, whereas Ferreira et al. [4] and Leedekerden et al. [9] use scanning laser range finders and sonar to produce high-resolution 3D maps of the above and below water environment. Cameras have also been proposed for detecting specific objects on the water [2, 4]. Scherer et al. [14] have used cameras and laser scanners (albeit on an aerial robot) to map the edges of waterways and the free-space above the water as the robot traverses them. Whilst high-resolution sensors such as lasers and sonar can provide robust navigation capabilities, for persistent monitoring their power consumption can be a particular challenge. Exploiting lower power, and cost, sensing modalities such as vision and ultrasonics to provide sufficient obstacle detection capabilities is a goal of this research.

The overall coordination of the mobile sensors (robots) is critical to accurately measure spatiotemporal environmental processes. An emerging research area for ASVs is that of mobile adaptive sampling where the ASV can alter its trajectory to improve measurement resolution in space and time (e.g. [17]). The survey paper [3] summarises advances in robotic adaptive sampling for environmental monitoring. Past research has focused primarily on the Gaussian Process-based reconstruction of stationary processes using combinations of mobile and static sensors networks [8, 17]. Whilst demonstrating the ability to capture and reconstruct various parameter distributions, these studies offer simulation only or short duration small-scale experimental validation. Larger-scale adaptive coordination of mobile sensing assets (underwater gliders) has been considered for tracking large oceanographic plumes in [10, 15]. Developing and demonstrating multi-robot adaptive sampling algorithms for the large-scale monitoring and tracking of spatiotemporal environmental processes is an over-arching goal of this research.

3 The Inference Autonomous Surface Vehicle

This section describes the current *Inference* Robotic Adaptive Sampling system and the greenhouse gas sampling payload system as applied and evaluated in this paper.

3.1 High-Level Scenario

The *Inference* Robotic Adaptive Sampling system was developed with the goal of providing a shared resource of multiple networked ASVs to allow researchers to remotely evaluate new sampling algorithms on real-world processes over extended periods of time. A typical use scenario proposed for the system is outlined below:

1. The ASVs, each carrying a scientific payload, are deployed on a water body.
2. Based on a desired sampling protocol (e.g. random, adaptive) and process modelling requirements, new sampling locations are determined. This can be achieved either from a remote centralised, or an on-board decentralised process.
3. Determine which ASV goes to each of the updated sample locations. This may involve optimising a cost function (e.g. minimising energy and/or travel time, maximising solar energy harvesting).
4. Each ASV navigates to their commanded sampling location.
5. Each ASV takes its scientific measurement and reports it back through the network.
6. Repeat steps 2–5 until a termination condition is met.

The system described in this paper is working towards achieving this goal with a preliminary experimental evaluation of this scenario using a simplified random exploration algorithm as described in Sect. 4.



Fig. 2 One of the autonomous surface vehicles from the *Inference* system. The navigation sensors, computing and batteries are located underneath the two solar panels. The scientific payload is attached to the moon-pool opening underneath the camera. Note the pan-tilt dome camera visible was not used in this study, only the smaller USB camera directly in front of it

3.2 *Hardware Overview*

The Autonomous Surface Vehicles used in the multi-robot *Inference* system are custom designed for persistent and cooperative operation in challenging inland waterways. The overall hull shape (see Fig. 2) has four key features; (1) A low draft allowing traversal in shallow water, (2) open sides and low curved top deck to minimise windage and the associated drift when station keeping during sampling, (3) a large top surface area angled for maximising energy harvesting from the solar panels, and (4) a moon-pool (open centre section) with standardised attachment points to mount custom sensor packages. The overall dimensional and mass specifications for the ASVs are given in Table 1.

Table 1 Physical and performance specifications of the ASVs

General specifications	
Length	1.50 m
Width	1.50 m
Height (above waterline)	0.7 m
Draft	0.15 m
Weight	33 kg (without payload)
	External payload: 4 kg
Propulsion	2 × BlueRobotics T100 brushless electric thrusters
Power	12 V 20 Ah LFP battery
	2 × 40 W solar panels
Speed	Max: 2.3 ms ⁻¹
	Typical survey: 0.5–0.8 ms ⁻¹

Propulsion of the ASVs is provided by two BlueRobotics T100 brushless thrusters mounted at the rear of each side of the hull. These provide the forward motion as well as steering (through differential control) of the vehicles. The system is powered by a single 20 Ah Lithium Iron Phosphate battery and two 40 W solar panels. This limited energy capacity requires advanced path-planning algorithms to coordinate the ASVs for maximising energy harvesting as well as to meet the overall sampling objectives. These algorithms are current ongoing research and not considered in this paper.

The ASVs are required to autonomously navigate inland waterways using only their on-board sensors. Each ASV has a suite of low-cost navigation sensors which include a GPS, magnetic compass with roll and pitch, and a depth sensor for measuring bathymetry. Of particular importance is the ability to detect the water's edge and potential obstacles on top of the water. The obstacle sensors used in this study are a USB camera (Microsoft LifeCam) mounted above the moon-pool, and four Maxbotix ultrasonic range sensors mounted just under the leading and trailing edges of the top deck. These sensors are used to detect the edge of the water and at-surface structure such as reeds, trees and water lilies (see Sect. 4). To minimise power consumption and cost, typical scanning laser-based or radar sensors are not currently used, although they can be added if required in future scenarios.

The ASV's thrusters are controlled via a custom designed motor and sensor interface board. This system is capable of providing waypoint control and ultrasonic and depth sensor based obstacle avoidance. To facilitate vision-based obstacle avoidance, each ASV has an Odroid C1 ARM Cortex-A5 1.5 GHz quad core CPU running the Robotic Operating System (ROS) and OpenCV.

There are two communication systems on-board the ASVs. The first is a 2.4 GHz WiFi system allowing communication to a gateway located on a floating platform on the water storage. This gateway has a wireless router and 3G modem allowing bidirectional data transfer from a centralised server located at the Queensland University of Technology. The second is a 2.4 GHz wireless embedded system (XBee IEEE 802.15.4) allowing serial communication between each vehicle as well as with existing static floating sensor nodes located on the water body.

Each ASV is capable of carrying additional custom payloads weighing up to 4 kg. The payload is mounted under the moon-pool opening via six attachment bolts. Currently available payloads include gas sampling (see Sect. 3.3), multi-beam and profiling sonars, water sampling and a winch system for water column profiling. A six pin connector is provided for use by the custom payloads. This connector provides power as well as bi-directional serial communications via a standardised protocol for triggering sampling, and reporting sample completion and possible faults.

3.3 Gas Sampling System

The goal of this study is to measure greenhouse gas emissions (efflux) from the waterway. Figure 3 shows the self-contained greenhouse Gas Sampling System (GSS)

developed to autonomously measure both the diffusive and ebullitive efflux. This payload is mounted underneath the ASV via the moon-pool payload attachment points as described in Sect. 3.2.

The GSS (Fig. 3) automates the traditional manual chamber-based sampling process and consists of three primary components; (1) A frame allowing the lowering and raising of a chamber into the water, (2) a chamber fitted with a continuous methane gas (CH_4) sensor and purge valve, and (3) a physical gas sampling unit.

The process of sampling the greenhouse gas being released from the water to the atmosphere using the GSS is illustrated in Fig. 4 and consists of four steps. Firstly, the ASV navigates to the desired sampling location it goes into a *weak* station-keeping mode. This limits the control input to the motors to reduce any disturbance that may influence the CH_4 efflux at the expense of a slightly increased station bound. At this

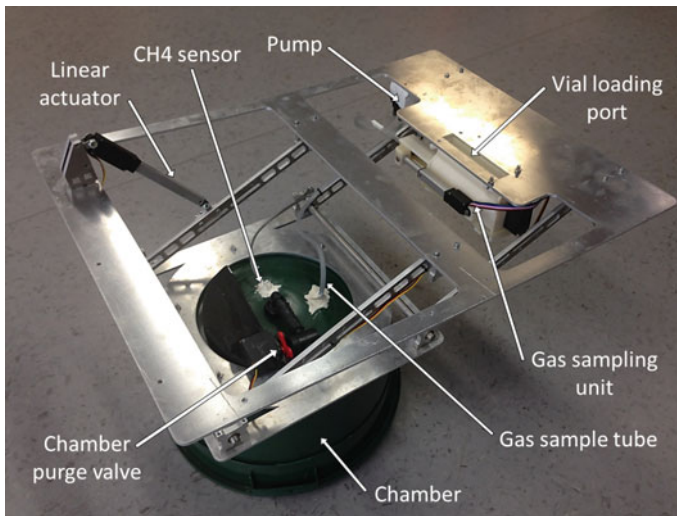


Fig. 3 The Gas Sampling System (GSS) used to measure greenhouse gas (methane) release to atmosphere from the inland water storages. The GSS is attached to the ASV as described in Sect. 3.2

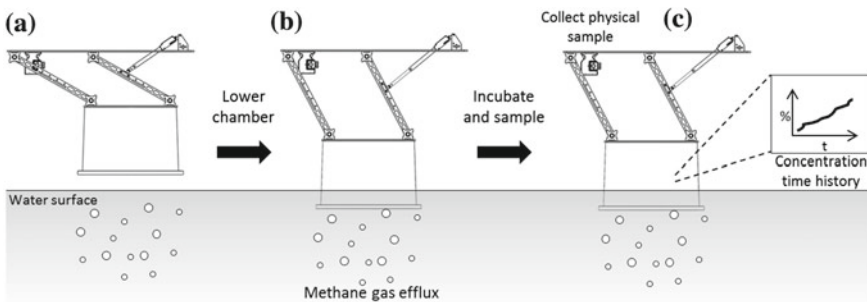


Fig. 4 The sequence of actions required to measure greenhouse gas using the GSS

point, the chamber purge valve (see Fig. 3) is opened and the chamber lowered using the linear actuator to achieve a desired air volume within the chamber (Fig. 4a–c). The second step involves closing the chamber purge valve and letting the methane concentration within the chamber increase for a predetermined *incubation* time (see Sect. 4 for a discussion on incubation time). During incubation, the methane sensor continuously measures the concentration within the chamber (Fig. 4b, c). At the end of the incubation, the third step (Fig. 4c) calculates the overall gas efflux rate from the gradient of the recorded methane concentration time history. Also a physical sample of gas from the chamber is collected for laboratory analysis using the gas sampling unit (see Fig. 3). This involves a sequence of actions that firstly purges the sample tube using the pump, then loads a pre-evacuated 12 mL vial into the sampling unit. A linear actuator on the unit drives a hypodermic needle into the vial whilst pumping gas from the chamber. Once 20 mL of gas has been pumped into the vial (over pressure sampling technique), the needle retracts and the unit discharges the vial ready for the next sample.

After sampling is completed, the final step involves opening the chamber purge valve and raising the chamber out of the water. At this point the ASV can move to the next sample location.

4 Technical Approach

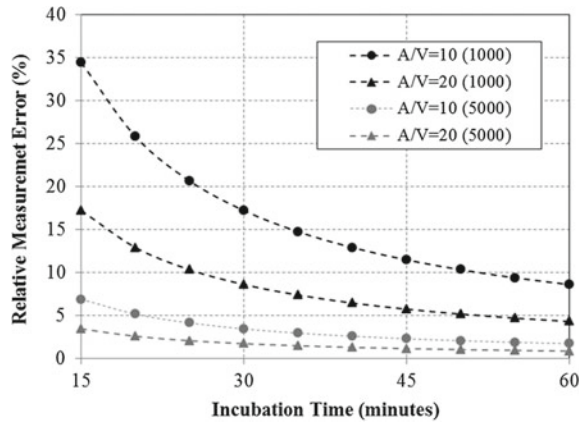
This section outlines technical details relating to the sampling of greenhouse gas (methane), obstacle avoidance, and the sample site selection algorithms used for coordinating a number of the ASVs across a previously unexplored water body.

Gas Sampling Protocol

During the sampling phase, the concentration measured by the methane sensor is polled every 2 s for the entire incubation period. A linear least squares line of best fit applied to this time history and the gradient used to calculate the flux rate.

A key consideration for greenhouse gas sampling is determining the minimum incubation time that maximises detection accuracy. The output from the continuous methane sensor in the GSS is quantised to 0.01 %. While diffusive fluxes are typically less than $50 \text{ mg m}^{-2} \text{ d}^{-1}$, ebullitive fluxes in our region can be as high as $22,000 \text{ mg m}^{-2} \text{ d}^{-1}$ [6]. Varying the incubation time and/or head-space ratio (i.e. the ratio of chamber surface area (A_c) to its internal air volume (V_c)) can be used to achieve a desired detection accuracy. Figure 5 shows the predicted variability in relative measurement error (i.e. the percentage error between a true methane flux to that which can be measured by the GSS) versus incubation time for different methane efflux rates and head-space ratios. As can be seen, longer incubation times lead to reduced errors as with increasing head-space ratios. However, longer incubation times mean less sample points can be performed per day. In this study, the primary

Fig. 5 The predicted percentage relative measurement error of methane flux rate with incubation time for the prototype GSS (see Sect. 3.3) with a sensor output resolution of 0.01 %. Two efflux rates are considered, 1000 and 5000 $\text{mg m}^{-2} \text{d}^{-1}$ with head-space ratios (A_c/V_c) of 10 and 20 m^{-1}



interest is the detection of methane “hot-spots”, that is where it is bubbling from the water. Therefore, incubation times of 15–20 min were chosen here to allow detection of methane rates as low as $1000 \text{ mg m}^{-2} \text{d}^{-1}$, albeit at lower accuracy. However, the higher the efflux rate, the more accurate the measurement.

Obstacle Avoidance

The ASVs have three sensors for obstacle avoidance; (1) ultrasonic sensors, (2) a camera, and (3) water depth sensor. The ultrasonic sensors have a maximum range of 6.5 m and are used to detect above water objects in front of the ASV such as land, reeds, trees and larger buoys. The camera, only used when moving between sample waypoints, is used to detect water lilies on the water’s surface. The image stream is processed at 1 Hz. With the camera fixed to the ASV, the horizon can be approximated and only the scene below the horizon considered. Image segmentation is conducted using an empirically determined threshold on the green and blue color channels with an approximate water lily size threshold to reduce noise. Figure 6 shows an example image from an ASV and the resulting segmentation of the water lilies (shown in red).

To detect shallow, non-traversable water, the depth of water below the ASV is continuously monitored. The outputs from all obstacle sensors are parsed by the on-board controller. When a detection occurs, the ASV trajectory is modified as described in the following section.

Multi-robot Sample Site Selection

A random walk-based algorithm is proposed here for selecting locations for n ASVs to sample the environment in an attempt to identify regions with high methane gas flux. There are two key assumptions: (1) the boundary of the water body is known from sources such as GIS, and (2) the ASVs can communicate between each other



Fig. 6 Example of image segmentation from the ASV for detecting on-water obstacles such as water lilies (*Left* original image. *Right* image with detected obstacles highlighted in red)

and can share their list of previous and next sample locations. In this study, we do not use bathymetry but it could be used in the future to help guide the algorithm.

The selection of new sample locations is based on an online random walk and potential fields. Iterating through each robot, the basis of the algorithm is as follows:

1. All previously sampled sites for all robots are represented as 2D Gaussian potentials centred at those points with fixed amplitude and standard deviation.
2. A random position at radius r from the current position is selected. If this position is not on land, and the value from the closest Gaussian potential is less than a threshold, this becomes the next sample point for that robot. If this condition is not met, the process is iterated until a location can be found. If no location can be found after a set number of iterations, the search radius is increased by Δr and the process repeated until a site is found or some termination criteria is met.
3. To increase local intensification of sampling in methane “hot-spots”, if the measured flux rate at the robot’s current location exceeded some threshold, the search radius for the next sample step is set to βr where $(0 < \beta \leq 1)$ and the potential threshold trigger relaxed.

During waypoint execution each robot drives in a straight line towards the goal. If the water depth falls below a threshold (i.e., too shallow), or an obstacle is detected, the vehicle starts to move either clockwise or counter clockwise around the contour until a new straight line to the goal can be achieved. This entire process is repeated for all robots until a desired number of samples are collected or some other termination condition met.

5 Results

An experimental evaluation using two ASVs with gas sampling payloads was conducted on two water reservoirs in South East Queensland, Australia; (1) Gold Creek Dam, and (2) Little Nerang Dam. These are established study sites and selected as

they exhibit regions of significant methane ebullition and provide a range of challenging operational conditions for evaluating robotic systems.

Previous studies [6] had collected georeferenced outlines of the water's edge (boundary) as well as bathymetry maps for both sites. Only the boundary was used in this study for implementing the sample site selection algorithm described in Sect. 4. Figure 7 shows the two ASVs used in this study on Gold Creek Dam.

The first experiment was conducted at Gold Creek Dam. This is a small, relatively open dam with a narrowing distal arm. The sample selection algorithm was run to collect 12 samples for each ASV, with a step radius of 100 m, and intensification factor of 0.5. The trigger was set at $1000 \text{ mg m}^{-2} \text{ d}^{-1}$ with 20 min incubations. The time to complete the sampling was approximately 5 h. Figure 8 shows the results of implementing the sample strategy for both ASVs. These results show the ASVs were capable of navigating the water storage and implementing the sample protocol. The online detections of methane exceeding the trigger threshold (markers in yellow) correspond to areas physically observed to have methane ebullition. As ebullition is essentially a point source emitter, there can be extreme variability even at short spatial and temporal scales (see [6]). Therefore, whilst ebullition can often be seen in expected regions (e.g. top image of Fig. 8) a sample within that region does not always guarantee the capture of gas bubbles sufficient to achieve high rates.

A second experiment was conducted at Little Nerang Dam. This is a longer and narrower water storage with a steep sided catchment. The sample selection was run with a total of 30 samples for each ASV, step radius of 200 m and an intensification factor of 0.5. The trigger was set at $1000 \text{ mg m}^{-2} \text{ d}^{-1}$ with 15 min incubations. The time to complete the experiment was approximately 10.5 h.

Figure 9 shows the results of implementing the sample strategy for both ASVs. These results again show the ASVs ability to implement the sample protocol and



Fig. 7 The two ASVs at the start of a sampling campaign on Gold Creek Dam, Queensland. The retracted gas sampling unit is visible underneath the ASV on the *right*

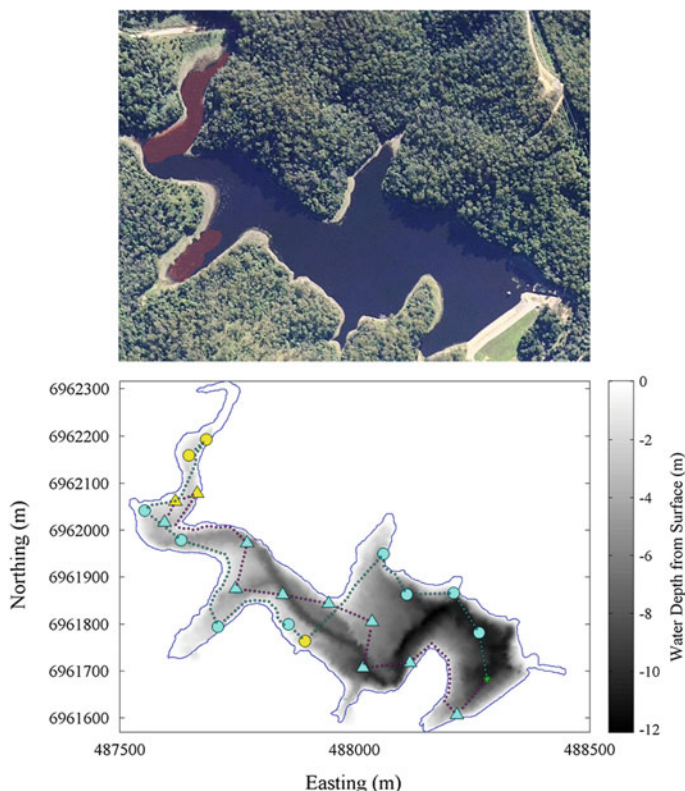


Fig. 8 Sampling locations and ebullition detections from 20 min incubations using two ASVs on Gold Creek Dam, Queensland. *Top* An aerial image of Gold Creek Dam with red overlay showing the regions of physically observed methane ebullition. *Lower* The trajectory and resulting sample locations indicated by the circles for ASV1 and triangles for ASV2. The start location for both ASVs is indicated by the green dot. The circles and triangles highlighted in yellow indicate the online chamber measurements that exceeded $1000 \text{ mg m}^{-2} \text{ d}^{-1}$

navigate the water storage. The online detections of methane exceeding the trigger threshold (markers in yellow) are consistent with previous research at the dam [6].

Whilst these experiments demonstrated the system for real-time sampling of greenhouse gases across water bodies, the online component of gas sampling system was not optimised for detecting lower (and more common) flux rates of less than $1000 \text{ mg m}^{-2} \text{ d}^{-1}$. Future work will look at adaptive chamber head-space control as well as higher precision sensors to improve the utility of the system for accurate quantification of the combined diffusive and ebullitive flux of greenhouse gases.

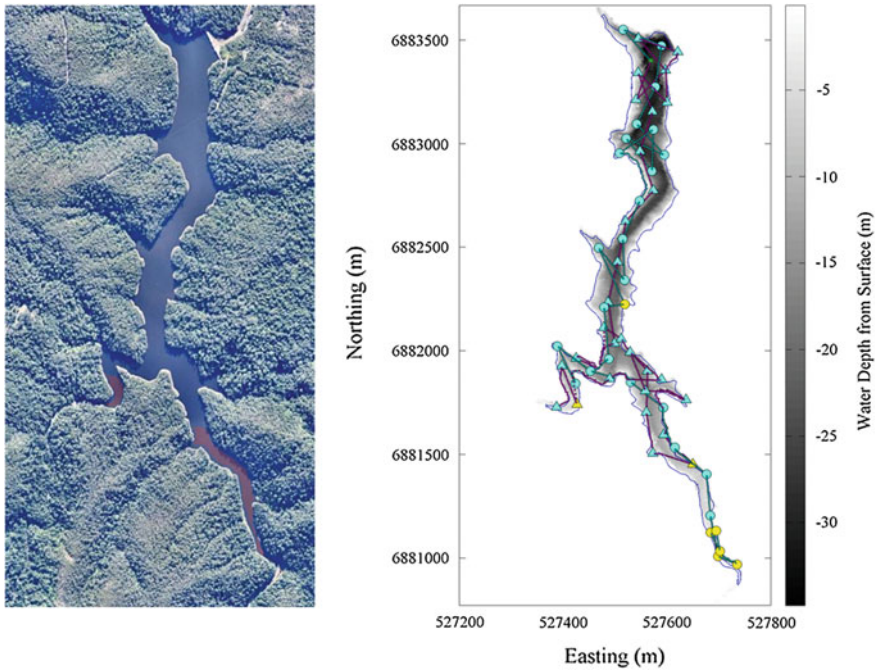


Fig. 9 Sampling locations and ebullition detections from 15 min incubations using two ASVs on Little Nerang Dam, Queensland. *Left* An aerial image of Little Nerang Dam with red overlay showing the regions of physically observed methane ebullition. *Right* The trajectory and resulting sample locations indicated by the *circles* for ASV1 and *triangles* for ASV2. The start location for both ASVs was at the dam wall located at the northern most end. The *circles* and *triangles* highlighted in *yellow* indicate the online chamber measurements that exceeded $1000 \text{ mg m}^{-2} \text{ d}^{-1}$

6 Conclusions

This paper has presented a novel robotic sampling system for conducting large-scale, persistent monitoring on complex inland waterways. The system, named *Inference*, consists of multiple networked Autonomous Surface Vehicles (ASVs) carrying a range of scientific payloads. Experimental results demonstrate the ASV's ability to navigate complex waterways whilst executing a multi-robot online sampling protocol. Using a custom Gas Sampling System (GSS) attached to each ASV, experimental results also show the robotic system is capable of measuring and localising strong greenhouse gas release (methane) to atmosphere. Future research is focused on developing more sophisticated multi-robot adaptive sampling algorithms to achieve persistent monitoring and mapping of spatiotemporal processes whilst considering energy, speed and sampling constraints of the vehicles. Additionally, new sensors and algorithms for head-space control of the GSS are being developed to improve its lower detection limit for sampling regions with low gas flux rates.

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