Bubble Watch: AI-powered estimation of methane emissions from river seeps

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[1] CSIRO. “Methane seeps in the Condamine river,” Accessed: Jan. 13, 2026.
[2] Kaiming He Georgia Gkioxari Piotr Dollar Ross Girshick. “Mask R-CNN”. Facebook AI Research (FAIR) 2018.
[3] Harold W. Kuhn, "The Hungarian Method for the assignment problem", *Naval Research Logistics Quarterly*, **2**: 83–97, 1955

Problem

Methane seeps can release gas into rivers, visible as persistent bubbling at the surface (Figure 1).

Quantifying emissions is difficult because seep activity can be spatially patchy and highly variable over time.

- Methane is a potent greenhouse gas → improved quantification supports **emissions accounting**.
- Field measurements can be **labour-intensive** and **unsafe** → remote monitoring improves safety.
- Better temporal coverage reduces **bias** from snapshot measurements.

Figure 1: In the Condamine River region, methane released from underground geological sources rises through the riverbed and vents at the water surface.

Previous Work and Research Gap

Existing approaches: flux hoods/chambers provide direct measurements but require repeated field deployment (Figure 2). Remote sensing and surveys can locate seep activity but don’t directly provide continuous flux.

Gap: Overhead surface video is attractive but challenging (glare, ripples, foam, turbidity, lighting). A validated mapping from **surface bubble signatures** → **flux** requires a novel approach.

Figure 2: Seeps have been observed and monitored near the Chinchilla Weir. Using floating flux hoods, environmental consultants investigated the seeps in a grid pattern where the amount of gas flux for a given time was recorded [1].

Aim

This project aims to improve how gas seeps in water are measured by combining **high-definition video** capture with **computer vision** to estimate emission rates from bubbling seeps. The method will first be developed and validated under controlled conditions using air injected into water, providing a foundation for later deployment on methane seeps in the field.

Approach

Develop and validate a computer-vision pipeline that estimates seep gas flux from **overhead HD video** by detecting bubble activity, extracting quantitative features, and mapping those features to **flow rate / flux**.

- **Video capture & preprocessing** (stabilisation, polarisation, thresholding)
- **Bubble segmentation** (deep learning → masks / frame)
- **Bubble tracking** (associate bubbles across frames)
- **Feature tracking** (count/area/size distribution over time)
- **Flux estimation** (calibration model: features → flux)

Figure 3: End-to-end workflow: from overhead imagery to quantitative flux estimate.

Deliverables

- A curated dataset of overhead bubbling videos from controlled experiments, including labelled frames for training and validation.
- A trained deep learning model capable of segmenting surface bubbles in HD video.
- A processing pipeline that converts video to estimated flow rate.
- Quantitative evaluation of model performance, including segmentation accuracy and flow estimation error under controlled conditions.
- Recommendations and a clear pathway for applying the method to real-world methane seeps and future drone-based monitoring.

Validation

Verification of the deep learning approach will begin in a controlled environment.

- Known air injection flow settings (ground truth)
- Overhead camera geometry like intended field view
- Repeat trials at multiple flow rates

Once the processing pipeline has achieved satisfactory results in the lab environment field data will be collected to further test the model’s robustness.

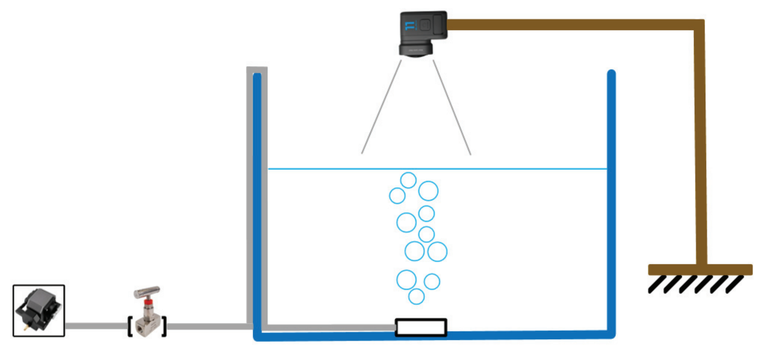

Figure 4: The controlled rig consists of an inlet air pump, a needle valve for finer control of inlet flow, a diffuser to generate bubbles and the camera for video capture.

Current Progress

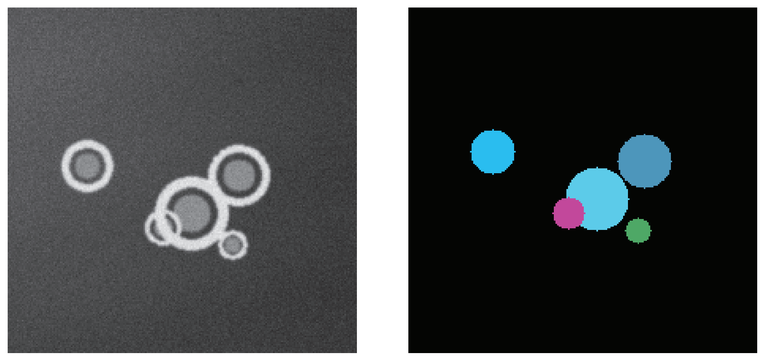

Figure 5: A synthetic dataset has been generated to start evaluating existing deep learning frameworks. The left image represents the synthetic bubbles, and the right image represents the masks associated with each bubble.

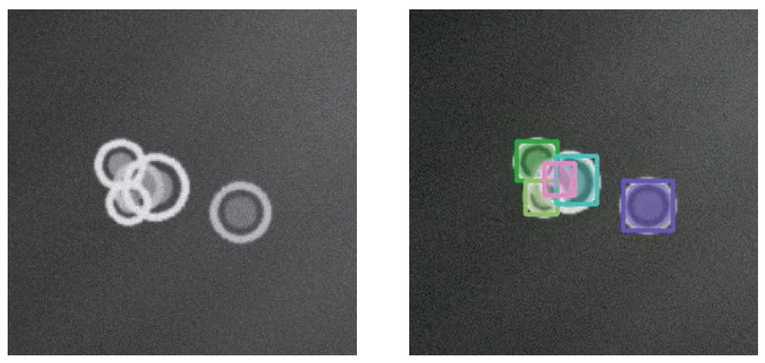

Figure 6: A **Mask R-CNN** [2] model was trained on 9600 training examples. The left image here shows an example of test data which was unseen during the training process. The right image shows the segmentation performed by the model.

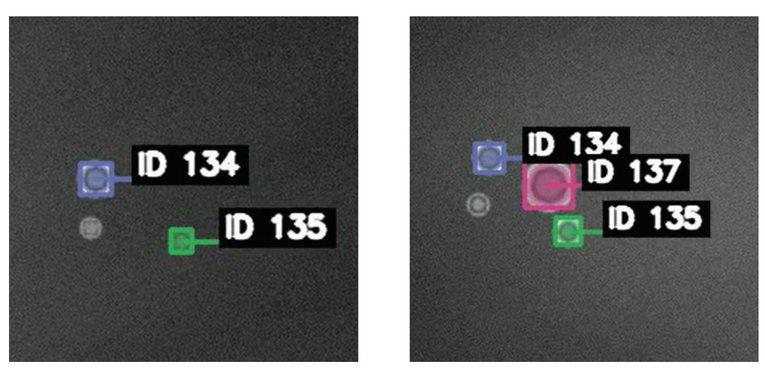

Figure 7: Tracking across frames is done using the **Hungarian algorithm** [3]. These 2 images are ~30 frames apart. In this example, one bubble is **not detected**, which can occur when its appearance becomes ambiguous and the detector’s confidence falls below the inference threshold.

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