PoMELO Passive Blind Test Results: Emissions detection and quantification

Thomas E. Barchyn[*,1], Michelle Clements[1], Tyler Gough[1], Chris H. Hugenholtz[1], Abbey Munn[1], Joseph Samuel[1], Clay Wearmouth[1], Coleman Vollrath[1]

[1]Department of Geography, University of Calgary, 2500 University Drive NW, T2N 1N4, Calgary, Alberta, Canada

*email: tbarchyn@ucalgary.ca

This manuscript is a non-peer reviewed preprint submitted to EarthArXiv.

Abstract

PoMELO Passive is a technology that combines vehicle-based pollution measurements from public roads with cloud-based software to: (i) detect emissions from oil and gas sites, and (ii) quantify emissions rates. Automated attribution and plume modeling algorithms provide results with little human intervention, facilitating large scale monitoring programs. PoMELO Passive is operationally deployed at the University of Calgary as part of its pan-Canadian methane monitoring program.

To evaluate performance, the system underwent a blind test program assessing detection and quantification performance. Tests were administered by the Alberta Methane Emissions Program (AMEP) at the Carbon Management Canada Newell County Test Facility, near Brooks, Alberta, Canada from 23-27 September 2024.

Tests were conducted in a blind configuration where release rates were blind to the University of Calgary. Detections and quantifications were produced by the Passive system, then reported to AMEP. Finally, real release rates were un-blinded, facilitating analysis and reporting. Localization performance was not evaluated. Release rates varied from 0.0 g/s to 2.49 g/s CH_4 and were metered with a mass flow controller prior to release from a single stack. A total of 190 independent single-release, single-pass experiments were performed.

Detection results indicate that PoMELO Passive effectively detected 60% to 85% of the releases < 1 g/s, and 88% to 100% of the releases > 1 g/s. There were no false positive detections. Non-detects primarily occurred in situations with low wind speeds (< 3 m/s), suggesting detection was modulated by environmental conditions.

Quantification results were assessed at the single- and multi-pass scales to simulate opportunistic and targeted sampling. Single-pass quantification results had little systematic bias, but some variability (linear model slope = 0.927, $r^2 = 0.70$). Replicates of individual release rates were aggregated to assess quantification improvement with averaging multiple plume passes. Multi-pass results similarly had little systematic bias, but less variability (linear model slope = 1.05, $r^2 = 0.95$).

Broadly, PoMELO Passive can produce high quality data in a low-cost and highly scalable deployment model. However, data users require effective tools to carefully manage uncertainty and make full use of data in assimilation and analysis systems.

1 Introduction

Measuring pollution sources from adjacent roads using instrumented vehicles has been a widely used and effective method for more than a decade (see reviews Fox et al., 2019; Vollrath et al., 2024). The method is inexpensive and capable of producing data without requiring site access. Vehicle-based pollution monitoring can also be done passively, where sensor packages collect data on vehicles performing other work. These characteristics have made it an attractive method for science studies (Caulton et al., 2018; Vollrath et al., 2024). Uptake into the private sector has been slower, partially due to the complexity of data processing, required expertise, and poor scalability associated with manual processing. PoMELO Passive is a software toolset that attempts to solve these issues, by creating scalable and production grade technology to conduct vehicle-based pollution monitoring at scale. The system presently provides the algorithmic backbone of an operational pan-Canadian methane monitoring system at the University of Calgary.

Among the most important applications, vehicle-based monitoring of methane—which has been identified as a pressing target for emissions reductions (see Vollrath et al., 2024)—is extremely useful for the upstream oil and gas industry, which is transitioning to a future of lower emissions production. The challenge for industry is understanding where and how much methane is being emitted. These data are essential to conduct effective mitigation, prove mitigations to stakeholders, and maintain social license to operate. Vehicle-based methane monitoring is well suited to help with this challenge. However, to build trust with users, independently validated performance data are required.

To meet a need for performance testing, the Alberta Methane Emissions Program (AMEP, see www.amep.ca) established a blind testing program at the Carbon Management Canada Newell County test facility. This report details blind detection and quantification results from a 5-day test campaign, providing important information on the expected performance of the PoMELO Passive system in broad deployments.

The blind protocol utilized here relied upon a sequence whereby true release rates were not disclosed until reporting was completed by the University of Calgary. Following disclosure, this report was prepared by the University of Calgary. All results are publicly available for audit or re-analysis (Barchyn, 2025). Note that only AMEP-disclosed data are utilized here.

First, we outline the use cases of PoMELO Passive to better contextualize the experiments. Then we detail the experimental methodology. Following this we present results. Finally, we discuss the data, explaining our interpretations in the context of theory, and add important learnings from this test program.

1.1 PoMELO Passive use case overview

The PoMELO Passive system is a software tool for detecting, localizing, and quantifying emissions from nearby oil and gas sites using data from the PoMELO vehicle-based methane monitoring system. It is helpful to overview the broader context of methane measurement technologies and better explain how vehicle-based systems are used. This use case overview is important to explain how the tests were designed and what the results indicate.

There is a wide diversity of methane measurement techniques in application (see review from Fox et al., 2019, and Caulton et al., 2018). Satellites offer a synoptic perspective and can measure sites without operator involvement but suffer from issues with minimum detection limits and poor ground resolution (Sherwin et al., 2024). Satellites are generally useless with any cloud cover—a relatively common occurrence globally (Gao et al., 2023). Aircraft-borne sensors tend to provide site- or equipment-scale data but are expensive to operate and measurements are only provided by a few select companies (El Abbadi et al., 2024). Low-cost fixed sensors suffer from low quantification accuracy and false-positive issues (Ilonze et al., 2024), but are an area of active development that could yield future results. Most manual onsite measurement approaches (e.g., OGI, sniffers, drones) have extraordinary labour costs due to the detailed work required on each site (Fox et al., 2019), and require site access, a problem that can both reduce credibility and add considerable logistical expense.

The PoMELO vehicle-based system has two software packages that fit within this landscape. First, the University of Calgary version of PoMELO Padmapper software provides rapid equipment-scale emissions measurements on site (not assessed here, see Barchyn and Hugenholtz, 2020; 2022). Second, the PoMELO Passive software provides site-scale data, using data measured further downwind of a source (~ 100-1000 m) on nearby public roads. Table 1 provides an overview of the University of Calgary PoMELO software.

Table 1: *contrasting characteristics of PoMELO Padmapper (University of Calgary) and Passive software packages, presented to clarify the positioning of PoMELO Passive.*

	PoMELO Padmapper (University of Calgary)	**PoMELO Passive**
Measurement types	Detection, localization, quantification.	Detection, localization, quantification.
Measurement scale	Equipment	Site
Driving pattern required	Driving around oil and gas pads, within fenceline.	Driving downwind on nearby roads, outside fenceline.
Site access required	Yes	No
Downwind distance	< 100 m	> 100 m
Driver involvement	Required to operate software.	Not required, data can be collected without driver involvement.
Processing location	Onboard PoMELO vehicle system.	Cloud
Time from data collection to results	< 10 minutes	< 1 day (typically faster)
Typical work practice	Site by site guided leak detection and repair (LDAR).	Monitoring, measurement inventories, emissions analysis.
Driving speed	< 30 km/hr	30 – 140 km/hr
Ancillary measurements required	All required data are measured by PoMELO.	All required data are measured by PoMELO.
Performance data	Detection: Barchyn and Hugenholtz (2020). Quantification: Barchyn and Hugenholtz (2022).	Detection and quantification: this report.

PoMELO Passive has two distinct operational modes:

1) First, the PoMELO system can be used for *opportunistic sampling*. This means data are collected 'as is' without targeting. In some cases, the data produce quality measurements; in other cases, no data are produced. Opportunistic sampling is widely deployed in a situation where a PoMELO system is

running on a vehicle, but the operator is focused on other tasks such as navigating between oil and gas sites. Opportunistic data collection at the University of Calgary has been the backbone of a major monitoring program with PoMELO Passive and provides extremely low-cost data. It is not possible to choose where the data are collected with opportunistic sampling.

2) Second, the PoMELO system can be used in *targeted sampling*. In this mode, operators drive the system into specific locations to target certain sites. Replicate downwind passes are completed to create better quantification estimates through averaging. For additional background information, see Gao et al. (2022).

We use these two operational modes to guide testing and develop performance metrics. While we do not consider other operational modes, our results could be used to contextualize PoMELO Passive performance in variants. We do not artificially consider a situation where onsite wind data were available as while this would certainly improve results, it is not practical to deploy at scale (c.f., El Abbadi et al., 2024).

2 Methods

2.1 PoMELO Passive technical description

PoMELO Passive uses raw data from the PoMELO measurement system, which collects data from three sensors: (i) Li-Cor 7700 open-path methane sensor, (ii) RM Young 86000 sonic anemometer, and (iii) Hemisphere V123 GNSS / Orientation sensor (see Figure 1). The data are fused onboard the PoMELO system at 10 Hz and transmitted to the PoMELO Passive software cloud for processing.

Figure 1: *the PoMELO vehicle system during tests. The PoMELO data collection system is located on the roof of the vehicle and measures methane concentration, wind, and position. Once measured, data are sent to the PoMELO Passive calculation cloud. Additional details on the University of Calgary version of the system are available in Barchyn and Hugenholtz (2020; 2022).*

PoMELO Passive software has two main inputs: (i) raw PoMELO data, and (ii) known locations of sites that could be emitting. The data undergo quality control before segmentation, attribution, and ultimately ingested into point-source plume modeling algorithms. End data are then reviewed and delivered as results. The algorithms are proprietary and confidential to the University of Calgary.

In the blind experiments detections were interpreted manually in real time in the vehicle as local enhancements in methane concentration, to mirror a modality where operators detect results while driving, and to provide results immediately. Automated detection does exist in PoMELO Passive algorithms but is not evaluated here.

Quantifications were produced after the end of each survey day with Passive automated algorithms. Algorithms were sealed and remained constant with no human tuning or input. Due to quality control criteria, not all detected plumes were quantified—these quality control criteria were pre-programmed into the Passive software. Quality control algorithms evaluate collected data and flag situations that do not have data of sufficient quality to produce emissions quantifications. To summarize the analysis flow of each experiment:

1) The data were assessed to determine if a plume was detected.
2) If a plume was detected, PoMELO Passive algorithms evaluated quality control criteria.
3) If a plume passed quality control, a quantification was produced.

Thus, not all detected plumes produced emissions rate quantifications.

Results in this study are linked to the specific software version: *rc_22_sept_2024_v2*. Results are also specific to the PoMELO data collection system and sensors as PoMELO systems produce data with specific characteristics (see Billinghurst, 2024 for additional discussion).

2.2 Experiments

Experiments were conducted at the Carbon Management Canada Newell County Test facility, located near Brooks, Alberta, Canada (50.4575°, -112.1167°). The release stack was positioned in the center of a large field bounded by a perimeter road (see Figure 2). The PoMELO system must drive through the plume to measure emissions. The perimeter road allowed experiments to be conducted in any wind direction and make efficient use of the test facility. Downwind distances varied due to the position of the release stack and changes in the wind direction (see experiment conditions for additional detail). Variability in downwind distances is normal and expected in normal operations.

The facility is flat with 50 cm high prairie grasses. Variations in site topography was limited to ditches adjacent to roads, a canal to the east, and minor meter-scale variations in prairie topography. There are only one or two small deciduous trees present in the study area. This topography is representative of many parts of southern Alberta, but we caution that experiments are not representative of regions with hills or trees.

Non-target sources were carefully assessed by the University of Calgary with the PoMELO system. All survey days involved assessment of any potentially interference from adjacent wells or facilities. All experiments were run in the absence of plumes from non-target sources.

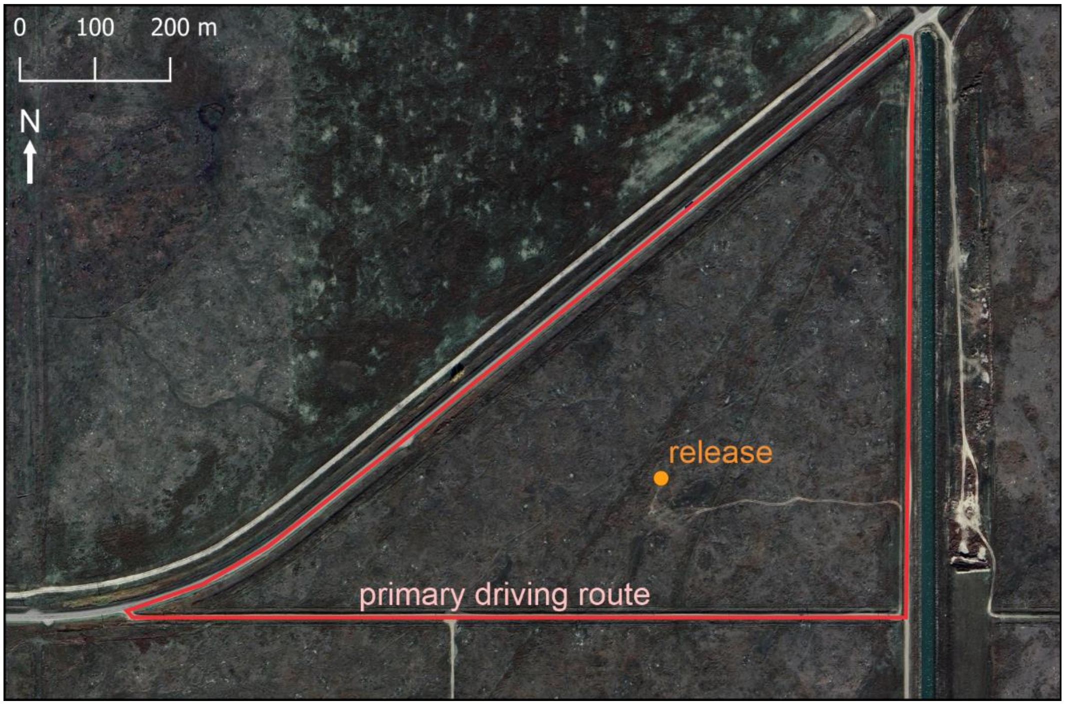

Figure 2: *the experiment situation at the Carbon Management Canada Newell County test facility. The release stack was in the middle of a field surrounded by the driving route to enable experiments with any wind direction. The road to the NW of the release stack was paved and resulted in much faster driving speeds (~ 60-90 km/hr) during experiments. Other roads were gravel or mud and necessarily required slower driving speeds (~ 30-50 km/hr).*

2.3 Release apparatus

The release apparatus (Figure 3) consisted of the following:

1) Compressed natural gas (CNG) tanks in a mobile trailer were used to supply gas. Releases were fed from one of the 16 tanks at a time. See Section 2.4 for details on the precise CH_4 content.
2) Gas was depressurized with several regulators to provide the flow controller with gas at a consistent pressure of approximately 64 PSI (441 kPa).
3) Gas then flowed through a heat exchanger to bring the gas temperature close to ambient temperature. This avoided feeding the flow controller cold gas and ensured the released gas was at ambient temperature, restricting any artificial lofting or sinking. Gas temperature was monitored at the flow controller.
4) An Alicat Scientific MCR 2000SLPM-D flow controller was used to control the flow rate and actively monitored during all experiments to ensure flow rates did not deviate from target rates. The flow controller has a specification accuracy of ± (0.8% of reading + 0.2% of full scale), which is largely negligible in comparison to error range of PoMELO Passive quantifications.
5) Gas flowed through approximately 10 m of tubing on the surface of the ground to the release stack. This helped ensure that gas temperature was close to ambient following the pressure reduction at the flow controller.
6) Gas then flowed to a vertical release stack that was 2.38 m tall where it entered the atmosphere and advected to where PoMELO could measure the plume.

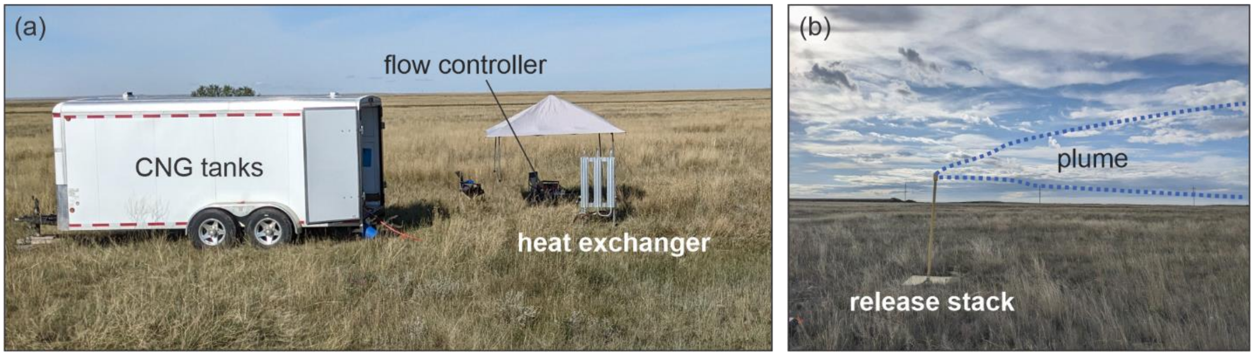

Figure 3: *release apparatus. Gas was routed from a mobile compressed natural gas (CNG) trailer through a heat exchanger, flow controller (a), then to a release stack (b).*

2.4 Gas analysis and flow controller setup

Gas was sampled multiple times from each CNG tank used in experiments. Gas was sampled using a water trap and evacuated bottles, then subsequently analyzed using gas chromatography. Any sample that had > 1% O_2 was assumed to be contaminated with air and discarded. From the valid samples, the C1 component was averaged and adjusted so average component sample percentages summed to 100%. This resulted in a C1 (CH_4) volumetric fraction of 90.52% CH_4 that was subsequently used to adjust released flow rates. Although gas was metered in bulk gas, all release rates reported here are expressed in terms of CH_4, not bulk gas.

The flow controller was programmed to set flow rate in Nm^3/day, with a pre-specified gas composition of CH_4 (91.79%), C_2H_6 (6.33%), N_2 (1.40%), and C_3H_8 (0.48%), which was predesigned to approximate the expected gas composition. It was impossible to use the sampled gas concentration in the flow controller gas chemistry as samples were taken during experiments and analyzed following fieldwork.

2.5 Blind protocol

AMEP and the University of Calgary worked together prior to the experiment to design an experiment protocol that would be representative. To ensure experiments remained blind, the following sequence of data exchange was used:

1) Rates were selected by AMEP staff and kept confidential.
2) Experiments were conducted by AMEP staff, with University of Calgary blind to release rates.
3) University of Calgary reported results.
4) AMEP provided results to the University of Calgary.
5) University of Calgary prepared this report.

Generally, the goal was to simulate methane emissions rates that are representative of typical site-scale emissions, and thus relevant to the oil and gas industry. Rate selection started with consideration to meet the mandate of the AMEP program, which necessitated results to be relevant to typical site-scale emissions in Alberta, Canada (< 500 m^3/day). To further constrain rates, AMEP and University of Calgary met to provide feedback on appropriate minimum emissions rates. The goal was to ensure that PoMELO Passive could reliably detect and quantify releases and produce data that would be possible to assess performance. If AMEP selected release rates that were too low and dominantly below the detection limit of PoMELO Passive, experiments would be less useful for evaluating quantification algorithms. University of Calgary was aware of the apparatus that was used to release gas during experiments, thus had some knowledge of a feasible maximum emissions rate that could be released. University of Calgary was also aware that AMEP would release some replicates of certain rates and some rates would be zeros. Beyond this, University of Calgary had no knowledge of selected release rates.

University of Calgary staff were aware of the location of the release stack and consequently no localization algorithms were evaluated in this study.

For each experiment the following single-pass protocol was followed:

1) University of Calgary positioned the PoMELO vehicle upwind or crosswind of the release location to ensure no relevant data were collected in the plume. In cases of light and variable winds, the PoMELO vehicle was placed in a further upwind position and actively monitored to limit any potential of collecting data in the plume.
2) AMEP staff selected a release rate and set the flow controller. AMEP staff confirmed the flow rate converged to the desired rate and monitored the flow controller.
3) A ~ 2-14 minute delay was observed to ensure the plume developed and matured into a representative form over the distance from the release stack to the measurement location. The minimum delay time was 2 times the downwind distance from stack to road divided by the observed wind speed. Consequently, the delay varied with wind direction and wind speed. Although this was a minimum, most experiments had longer delay times and the transit of the vehicle through the plume was often minutes after the start of the experiment, further ensuring that the plume developed into a steady state form.
4) The University of Calgary PoMELO vehicle passed through the plume once at a representative driving speed for the road. The representative driving speed varied throughout the experiments based on the wind direction. The road to the NW of the release point (used in experiments where wind was from the S, SE, or E) was paved and the PoMELO vehicle was driven at normal highway speeds (~ 60-90 km/h). The roads to the E and S of the release point were gravel and mud and speeds varied based on road conditions (~ 30-50 km/hr). No double passes, or any extra data collection within the plume was allowed.
5) When the PoMELO vehicle system reached a point that was clearly upwind or crosswind from the release point, AMEP staff were notified that the experiment was completed, and the next experiment was prepared. The drive direction was varied throughout the day to minimize any potential for bias associated with drive direction.
6) University of Calgary staff logged whether a plume was detected and noted times to determine matching quantifications.

At the end of the day field data were digitized. Emissions quantifications were automatically generated by the Passive system after the final experiment of the day was completed. Quantification results were extracted from the database during the evening and matched to each experiment. Final reporting was completed daily and provided to the AMEP team by email. Some non-essential supplementary context data were provided to the AMEP team later to add to the public dissemination, including environmental data such as measured wind speed and distance from detection.

2.6 Multi-pass aggregation protocol

To simulate targeted sampling, single-pass replicates of a given emissions rate were aggregated to assess the improvement to quantification results. We used a Monte-Carlo sampling technique that accounts for many possible combinations of replicates. We performed the following sequence of analysis steps for each aggregation. We evaluate aggregations (n) from 2-15, where an $n = 2$ implies a rate is determined using 2 single-pass replicates of a given emissions rate.

1) For each emissions rate replicate, we first evaluated whether there were enough replicate experiments to meet the aggregation. For example, it is not possible to evaluate $n = 15$ passes for 2.48 g/s, where there are only 9 replicates. This differs from traditional bootstrapping where oversampling of populations can be performed.
2) If there were sufficient replicates, n random samples of the replicates were taken, an average computed, and the process repeated 10,000 times. This ensured that all combinations of subsamples were considered for a given emissions rate.
3) Replicate scaled residuals (difference between the replicate average and the real rate divided by the real rate) were accumulated into a population of estimates and described with descriptive statistics.

Note that this protocol does not use Bayesian updating to accumulate results using the native probability density functions from PoMELO Passive. It is possible that aggregation with the underlying probability density functions would be more accurate (Wigle et al., 2024).

2.7 Experiment context

Experiments were run from 23-27 September 2024 to ensure a diversity of conditions were encountered. A total of 191 single-pass experiments were run, with one experiment discarded due to issues with the flow controller, yielding 190 valid experiments.

Figure 4 shows experimental conditions. Temperature varied from 10.31 to 31.77 °C, representative of summer, spring, and fall on the Canadian prairies. These temperatures are not representative of winter conditions. Wind speed varied from 0.72 to 13.6 m/s, simulating a reasonable range of wind speeds. Detection distances ranged from 180.7 to 689.9 m, effectively simulating a representative range of downwind distances that Passive is functionally deployed at.

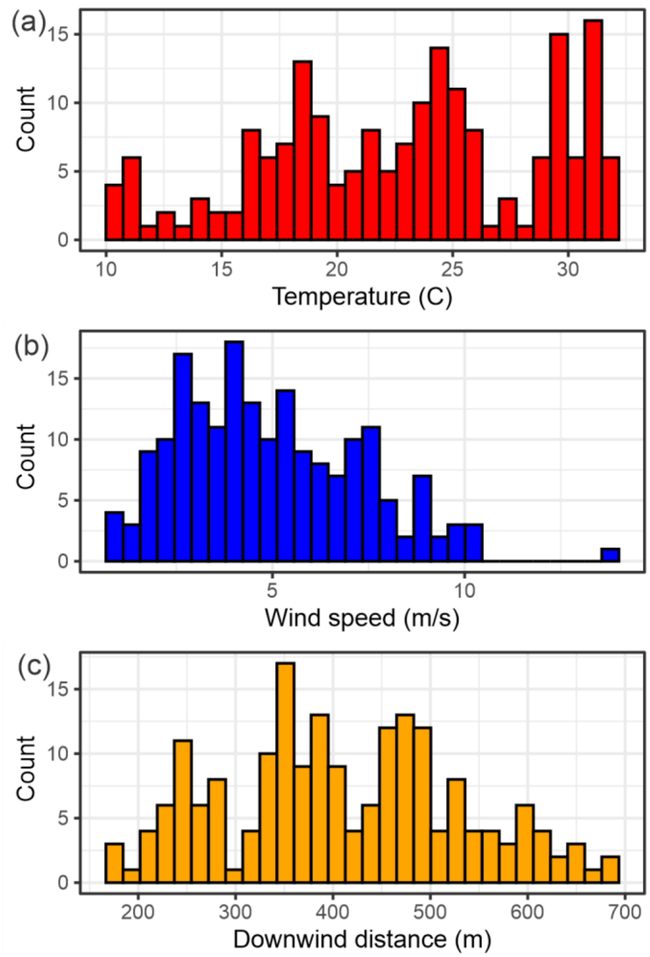

Figure 4: *environmental and experimental conditions for the single-pass experiments: (a) temperature, (b) wind speed, and (c) downwind distance.*

Release rates (Q_{crt}) were selected by AMEP staff and varied from 0 to 2.49 g/s. There were 16 zero releases (8.4 %). Release rate replicates were conducted at different times such that a given release rate would be encountered during different atmospheric conditions on different days (Figure 5a).

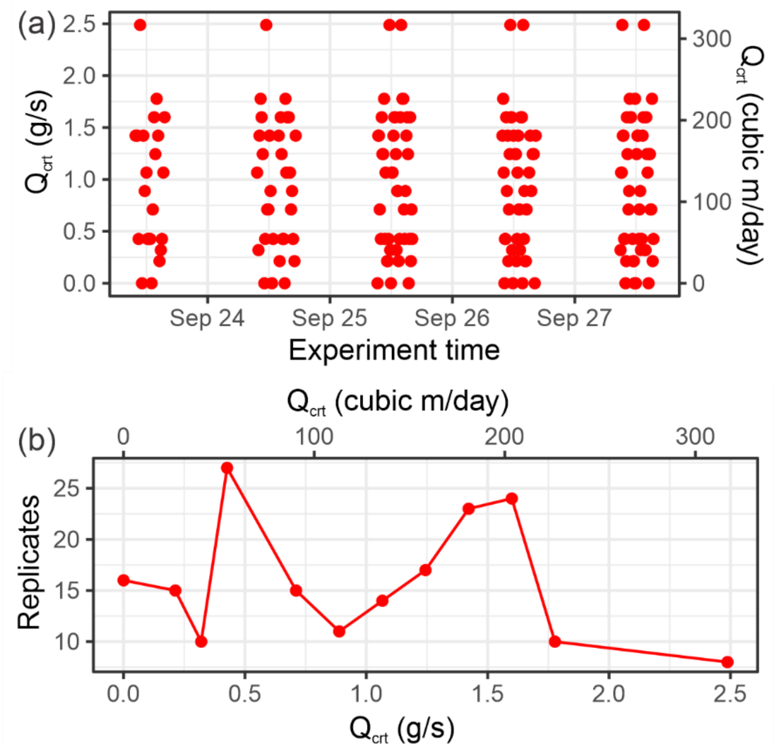

Figure 5: *release rate synthesis: (a) release rates (Q_{crt}) over the experiment, (b) number of replicates for each release rate.*

3 Results

3.1 Reporting and survey time

Final results were delivered to AMEP staff each evening following data collection via email. Detections were available immediately following each experiment, but quantifications required cloud processing and linking between experiments and automatic quantifications and resulted in delays. Most results were delivered within 4.5 hours from the final experiment of a day (Table 2).

Table 2: *reporting times for each experiment day. All times are local to Alberta at time of experiments.*

Date	Final experiment completed	Results reported via email	Delay from final experiment to final daily results (hr)
23 September 2024	15:34:00	19:16:00	3.7
24 September 2024	17:17:00	20:17:00	3.0
25 September 2024	16:06:49	20:31:00	4.4
26 September 2024	16:20:40	20:06:00	3.8
27 September 2024	15:24:58	21:24:00	6.0
AVERAGE			4.2

Survey times were not directly assessed due to the characteristics of the experiment. Survey time in the plume was always less than 30 s, but often much shorter as plumes at < 1000 m downrange tend to be less than 100 m wide and very quickly traversed by the PoMELO vehicle at typical driving speeds.

3.2 Detection

Detection results were evaluated within the replicates of release rates. Note that there was a different number of replicates for each release rate. There were no false positives. False negatives (missed detections) were more common with lower release rates. Detection performance ranged from 60% to 85% for release rates < 1 g/s, and 88% to 100% for release rates > 1 g/s (Figure 6).

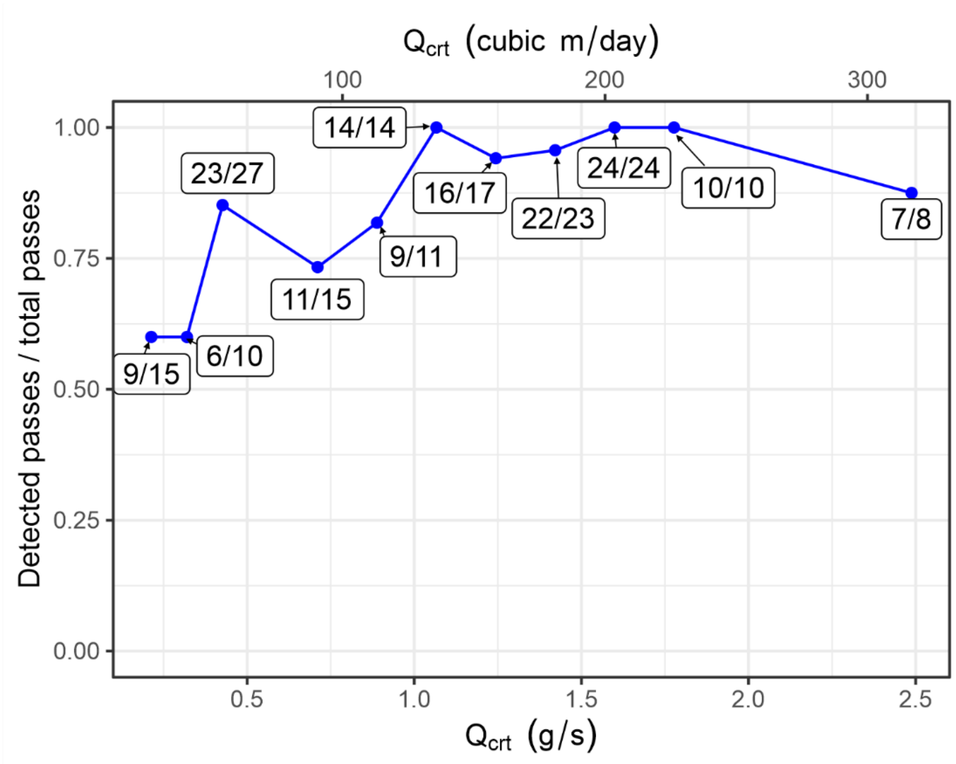

Figure 6: *detected passes / total passes plotted against release rate. The labels show the number of detected passes / total passes for each release rate replicate. Releases with zero emissions rate are not shown here. See Figure 7 and text for additional context on these results.*

Detection results can be contextualized against key measurement variables (Figure 7). The relationship with wind speed showed a trend where poor detection results were consistently found in situations with low wind speeds and low release rates. In particular, the only non-detect at the high release rate of 2.48 g/s occurred with a measured wind speed of 0.97 m/s. The relationship with downwind distance had a less clear relationship.

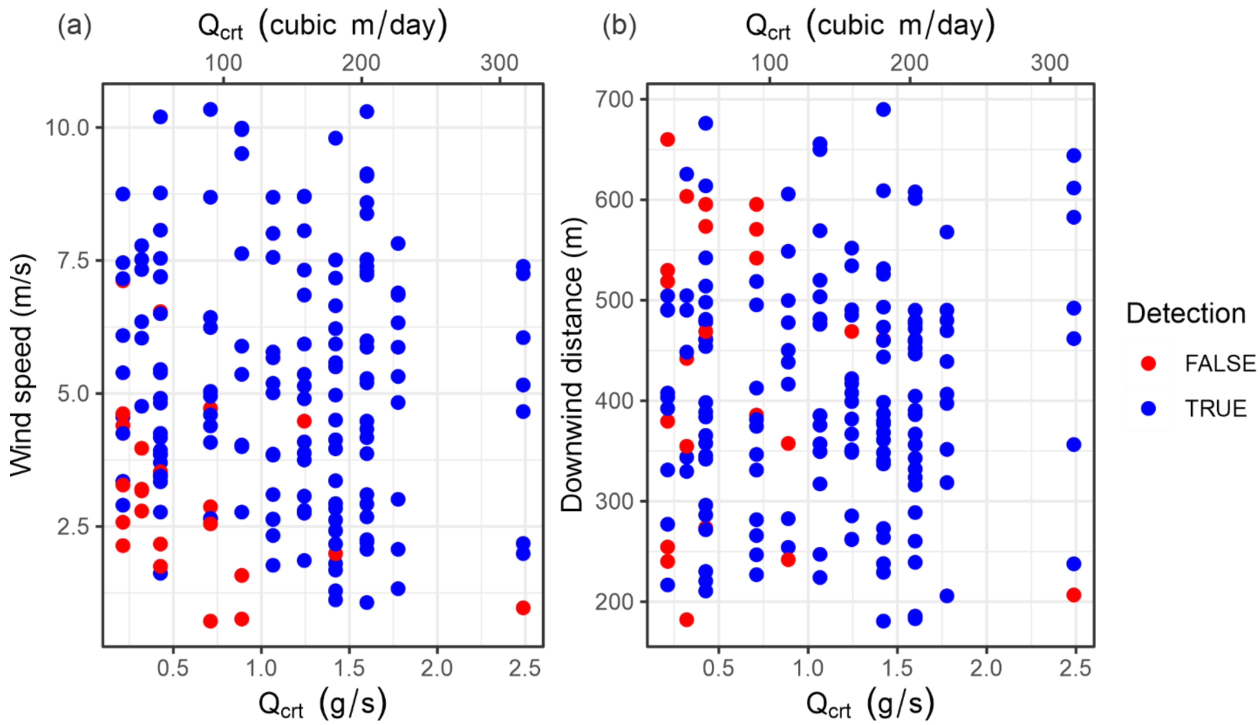

Figure 7: *detection results against key measurement variables: (a) wind speed, and (b) downwind distance. Detection was poor with low wind speeds and low release rates, and consistent when wind speeds increase. Detection did not have a consistent relationship with distance.*

We do not force a predictive equation on probability of detection here (c.f. Ilonze et al., 2025) for two reasons. First, we have relatively few data points at lower release rates in this experiment set, which would result in a relatively unconstrained predictive equation. This was a consequence of a focus on quantification performance within this experiment set. Second, there was a clear relationship with wind speed, suggesting that probability of detection should be analyzed with consideration of wind speed and reporting a minimum detection limit without explicit consideration of wind speed would misrepresent the probability of detection (see Ilonze et al., 2025; Thorpe et al., 2024). Following recent literature (see Thorpe et al., 2024 for overview), detection limits for PoMELO Passive are best considered in a functional form. However, these results do demonstrate that robust probabilities of detection occur with releases above 1.0 g/s across the environmental conditions tested here.

3.3 Quantification

3.3.1 Single pass

Of the 151 detections, 107 quantifications were produced (70.9%). Not all passes produced quantifications due to PoMELO Passive quality control criteria that do not report quantification results in situations with known poor performance or where quantification is not possible.

Single-pass quantification results compare released rates and predicted rates on a pass by pass basis. A simple linear model was fit to the data with a forced intercept of 0.0. The fitted slope was 0.927, $r^2 = 0.70$ (Figure 8).

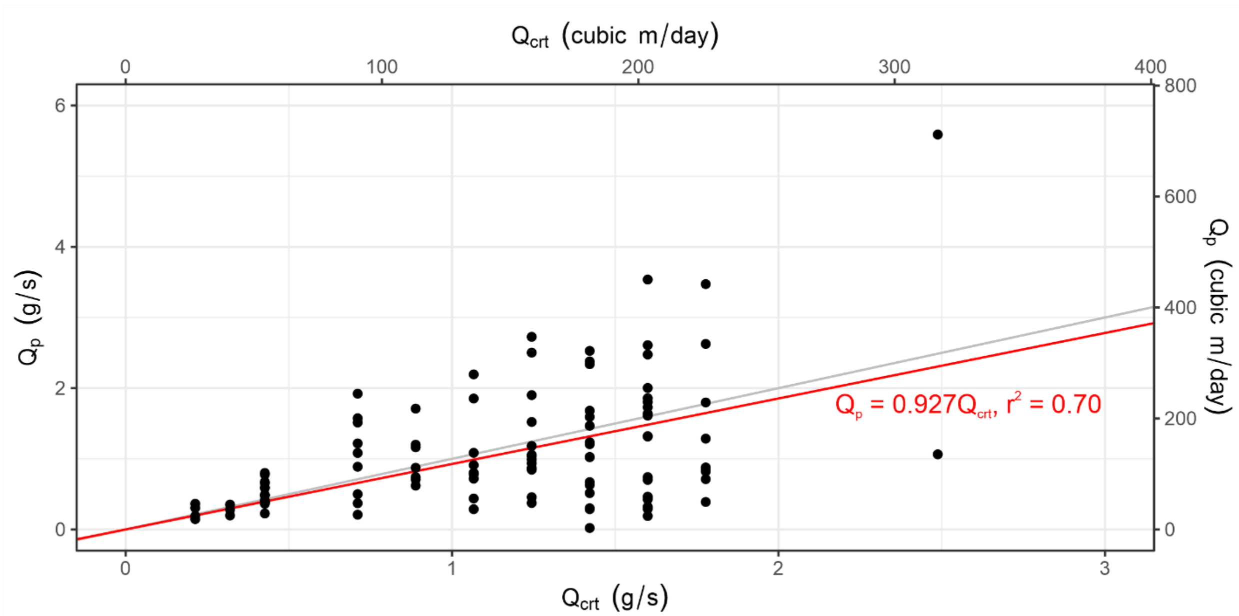

Figure 8: *single pass quantification results. The grey line is 1:1. The red line is a simple linear model fit. Error bars are not shown for clarity. Uncertainty is further explored in text. Note that not all detections produced quantifications due to quality control criteria that discarded plumes. For example, passes with a Q_{crt} of 2.49 g/s totaled 8 single-pass experiments, where there was only 7 detections and 2 successful quantifications. See Section 2.1 for additional information.*

Residuals scaled against the real release rate (($Q_p - Q_{crt}$) / Q_{crt}) provide a measure of the relative error (Figure 9). The relative frequency of residuals was generally clustered around 0.0 (perfect prediction), but there were some over- and under-predictions present in the dataset. There was little relationship with release rate or downwind distance. At lower wind speeds (< 4 m/s), there was a systematic under-prediction of emissions rate.

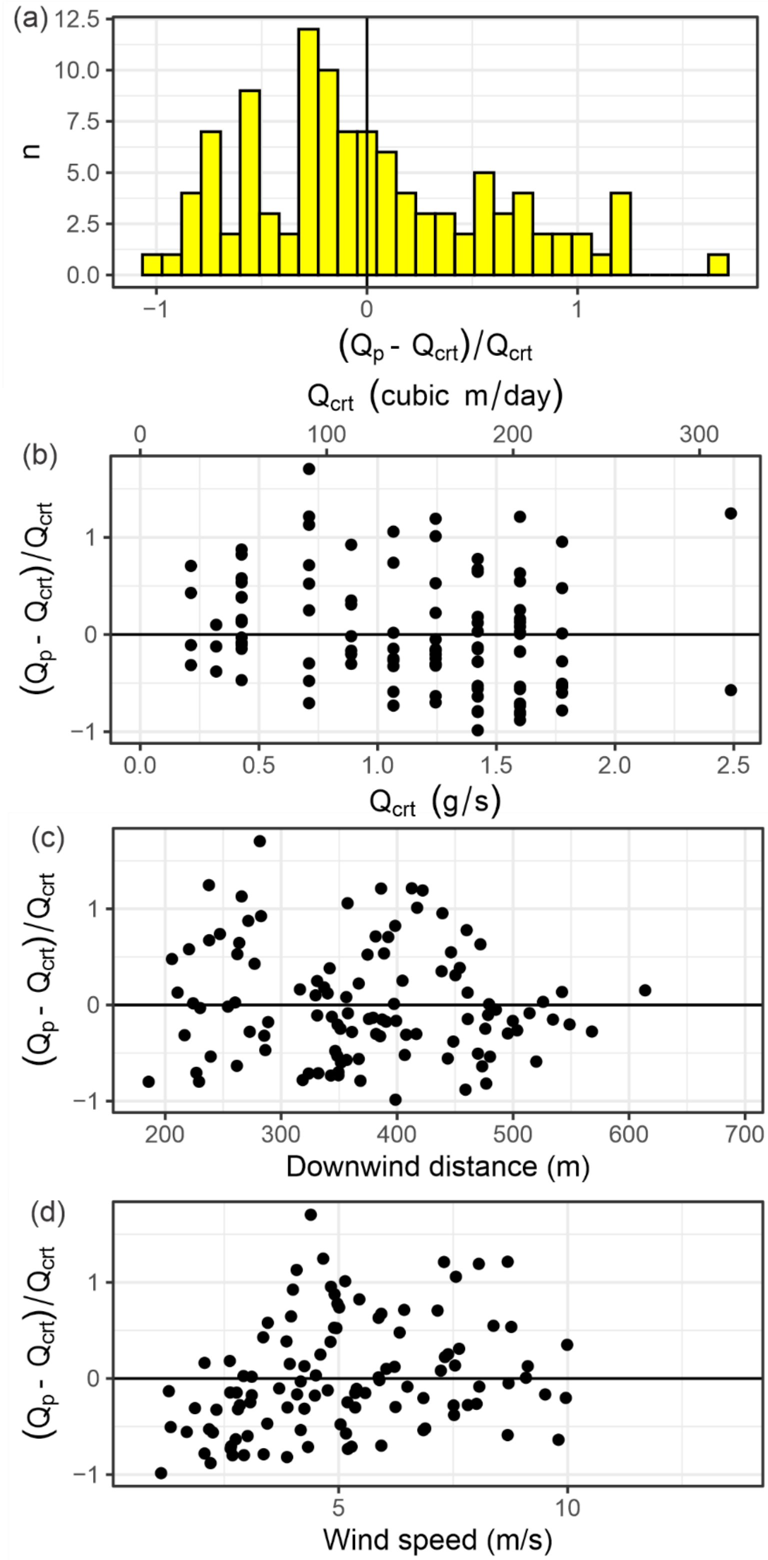

Figure 9: *characteristics of single pass quantification residuals. Residuals are expressed as predicted rate (Q_p), released rate (Q_{crt}). A residual of 0.0 indicates perfect prediction, negative values indicate underprediction, and positive values overprediction. Plots show: (a) relative frequency of residuals, (b) residuals against release rate, (c) residuals against downwind distance, (d) residuals against wind speed.*

3.3.2 Single-pass uncertainty prediction

PoMELO Passive predicts uncertainty for every emissions rate estimate. This uncertainty is specifically modulated for the measured environmental conditions, and as a result there is no universally applicable uncertainty estimate from PoMELO Passive. We can evaluate the uncertainty prediction with replicates to better understand the quality of predictions. Results reported to AMEP include 10%, 25%, 75%, and 90% percentiles of the underlying probability density function for each release rate (see Barchyn, 2025).

Real release rates within the predicted 10% to 90% percentile range should average at 80% of the experiments, in reality 88.8% of quantifications were within the 10% to 90% percentile range. Real release rates within the predicted 25% to 75% percentile range should average at 50% of the experiments, results here show that 56.1% of releases were within this range. Both ranges are slightly higher than predictions suggesting that uncertainty predictions are slightly more conservative than reality and real prediction accuracy is slightly better than the Passive uncertainty prediction model suggests.

3.3.3 Multi-pass

Multiple pass quantification results can be viewed by averaging results for each replicate emissions rate to explore how replicating measurements at release rates improves prediction performance (see Figure 10). A simple aggregation of all results from a given emissions rate provides an initial set of information on performance in situations where replicates of emissions rates were performed by PoMELO Passive (Figure 10). A linear model fit (with forced intercept of 0.0) had a slope of 1.05, $r^2 = 0.95$, indicating good fit but slight over estimation of real emissions.

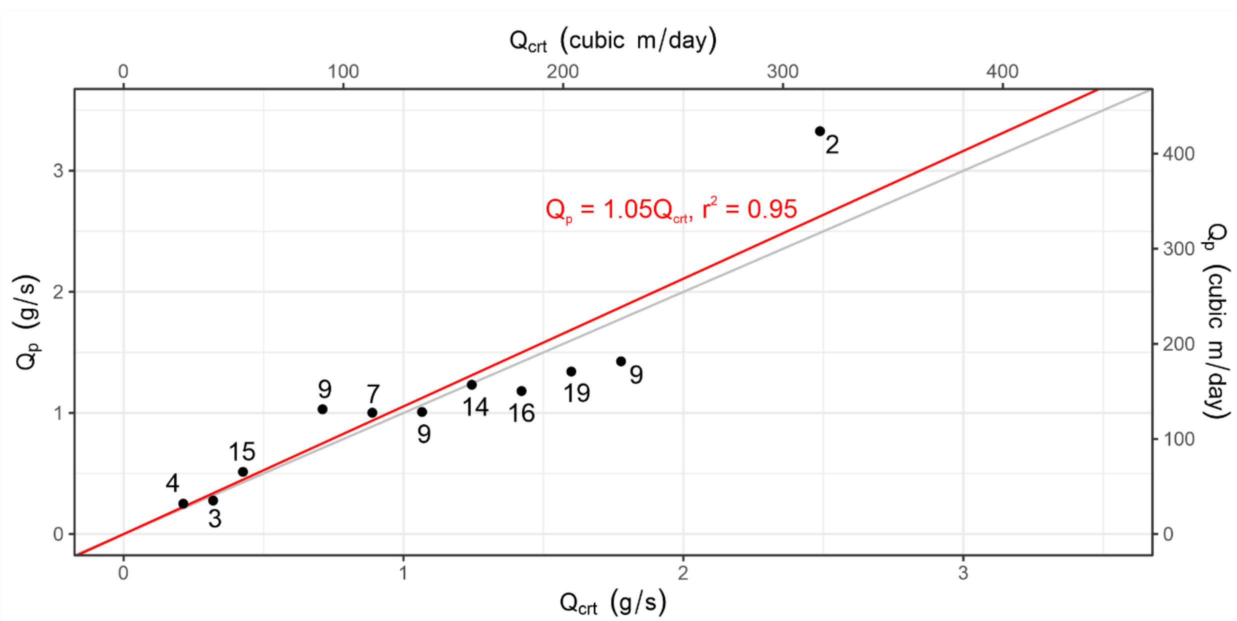

Figure 10: *quantification results for each release rate, averaged among all replicates. The grey line is 1:1. The red line is a linear model fit. Point labels correspond to number of single-pass experiments that were averaged to produce the data point.*

To further explore multi-pass data and better understand the impact of different aggregation schemes we evaluate the increase in accuracy that results from greater number of replicates. This is performed in a series of samples to account for different combinations of replicates, producing a probability density distribution (see Table 3).

Table 3: *the sample error distribution statistics with increasing aggregation (n). Increased number of passes produces more accurate results. See text for additional discussion and explanation.*

n	Percentile of sample error distribution $(Q_p\text{-}Q_{crt})/Q_{crt}$				Unique release rates included in sample
	10%	25%	75%	90%	
1	-0.59925	-0.38016	0.428592	1.011739	11
2	-0.43827	-0.23406	0.337098	0.487426	11
3	-0.38584	-0.1617	0.234948	0.40551	10
4	-0.35122	-0.16054	0.192838	0.377221	9
5	-0.33636	-0.1753	0.195649	0.37285	8
6	-0.29938	-0.16245	0.180841	0.354803	8
7	-0.2823	-0.15432	0.132648	0.363754	8
8	-0.27471	-0.1589	0.171152	0.37718	7
9	-0.22286	-0.19746	0.164362	0.450277	7
10	-0.2658	-0.174	0.117816	0.222803	4
11	-0.25414	-0.16658	0.102621	0.223002	4
12	-0.2447	-0.16499	0.100427	0.219782	4
13	-0.23194	-0.16396	0.105808	0.214737	4
14	-0.22141	-0.16256	0.086777	0.210365	4
15	-0.22521	-0.18016	0.204902	0.204902	3

The aggregation results table (Table 3) provides data on how increasing aggregation improves results. An aggregation of 2 ($n = 2$) corresponds to a situation where a given emissions rate was sampled twice. In this situation there is an 80% probability that aggregated results residuals will be within -44% to 49% of the true value (corresponding to 10% and 90% percentiles). In the situation of 6 passes ($n = 6$), there is an 80% probability that aggregated results will be within -30% to 35% of the true value. Results in Table 3 become less reliable with increased *n* as not all release rates could be used—a consequence of situations where *n* exceeded the number of passes available. In the case of $n = 15$, only 3 unique release rates could be used.

4 Discussion

4.1 Representativeness of conditions

An effective assessment of performance for any technology should mimic the real conditions where the system is deployed to ensure that the impact of conditions is factored into the performance assessment.

The Carbon Management Canada Newell County test facility is flat and has no trees. This is representative of Canadian prairie and United States Great Plains—but is not representative of other locations where there are trees or substantial topography. Both trees and topography have material effects on how the plume develops. Trees significantly increase surface roughness and can increase mixing and near surface turbulence. Topography has large impacts on near surface airflow, both by increasing near surface turbulence and creating systematic airflow patterns that are not accounted for in generic plume models like that used in PoMELO Passive. The effects of different surface and topography conditions on near-surface vehicle systems are not straightforward or possible to meaningfully generalize (Caulton et al., 2018). This noted, significant production basins such as the Permian, Denver-Julesberg, and many parts of the Western Canada Sedimentary basin have environments nearly identical to the facility used in these tests.

The release stack was a point, with a trailer, tent, a vehicle, and associated piping nearby (Figure 3). In general, this is representative of an upstream production site in Canada. Production sites often have several small buildings, separators, tanks, wellheads, and other low profile production equipment. The equipment is typically closely clustered (10s of meters) to minimize land use and cost—generally similar to our test situation. Releases of methane at real upstream sites can be sourced from different parts of the site, but given the long-range sampling here, this effect is unlikely to be a major source of error. Within site heterogeneities are important at close ranges (Barchyn and Hugenholtz, 2020; 2022), but less so at the distances relevant for PoMELO Passive. This generalization is stretched with gas plants or extremely large production sites which can more closely resemble area sources (with many release points) (Conrad et al., 2023) and where larger production equipment often create more atmospheric disturbance.

PoMELO Passive is not effective at measurement of flares, and these tests do not emulate flares. Flares (unlit and lit) are an important and easy to mitigate emissions source in Canada (Seymour et al., 2022). Flares fall into two categories, both of which are difficult to measure with PoMELO Passive: (i) unlit, which emit much higher rates than experiments here, and (ii) lit, which have methane emissions associated with incomplete combustion and characteristically thermally loft. This noted, it is likely that PoMELO Passive could intermittently detect these sources and, in some contexts, provide useful detection information.

Environmental conditions closely mirrored typical conditions on the Canadian prairies and United States Great Plains in summer, spring, and fall. We did not sample in conditions with temperatures below freezing, which are typical of winter. Despite this, the effects of environmental conditions can be more usefully discussed in terms of how the conditions affect the atmosphere. Much like other vehicle systems that sample a plume downwind of a source, detection and quantification suffers with vertical mixing. The reason is a lofting plume is difficult to predict, often under-sampled, and in some situations intermittently present at the surface (Caulton et al., 2018). Atmospheric instability and vertical mixing tend to occur preferentially in situations with strong surface heating (warmer temperatures) and low wind speeds. Both anecdotally, and with theory, PoMELO Passive is likely to have better performance in winter as winter conditions tend to have more stable atmospheres. As such, although winter conditions are under-sampled in this experiment set, theory suggests results could be better than those presented here.

Downwind distances measured here are representative of typical use cases of PoMELO Passive. Downwind distance has a strong theoretical influence on detection performance. Plumes mix laterally and vertically with increased downwind distance, causing lower enhancements that are, at some distance, indistinguishable from background methane variability. Detection performance at close ranges (< 100 m) with the PoMELO system is class-leading, and exceeds OGI (Barchyn and Hugenholtz, 2020), but gets lower and lower with increased distance downwind. To some extent the impacts of downwind distance effects are geographic and the characteristic downwind distances for a given production region are possible to geospatially analyze using tools similar to those used by Gao et al. (2022). We elaborate further on the known impacts of distance on detection performance below in Section 4.3.

4.2 Reporting and survey time

Reporting and survey time were reasonably quick compared to other technologies that require extensive manual processing, but slower than automated systems that operate within minutes of collection such as the PoMELO Padmapper system. Time to report is important in many contexts, particularly when the data yield follow-up action, emissions reductions, or there are bulk emissions penalties attached to the source.

Delays here are possible to sidestep in real operations. The PoMELO vehicle system has audible and visual cues when a plume is detected, thus detection results were available immediately after driving through the plume. Similarly, a simple qualitative quantification is entirely possible by looking at the methane enhancement and interpreting the conditions. From a practical perspective, an experienced PoMELO operator could instantly detect emissions from a nearby site and have a reasonable guess on whether the emissions are high or low.

As reporting times reported in Table 2 dominantly measure time to complete quantification, we can unpack the delays to explore the process. To quantify emissions with PoMELO Passive, data are transferred off-system and loaded into external databases (<1 hr), then processed (~1.5 hrs). In this experiment, we manually queried the results and matched the quantifications with each experiment by examining the result times (1 hr). Here, reporting times are a best-case scenario where staff time in the evenings was dedicated to this task. In normal operations, processing and any requirement of staff time could delay results delivery further.

This noted, these experiments do show that it is possible with PoMELO Passive to deliver quantification results within a few hours if there is sufficient staff and processing power. This is a powerful advantage of the system—but note that in some contexts the value of data can be diminished when delivered several hours after the fact.

4.3 Detection

Detection results (Figure 6, 7) indicated that PoMELO Passive was reasonably effective at detecting plumes at the rates released. We did not fit a pre-defined model to the data, as has been done in the past (Ilonze et al., 2025), because detection with PoMELO Passive is a function of multiple variables, not just emissions rate.

PoMELO Passive had no false positives. This was expected because detection with PoMELO Passive was done manually, and we were deliberately careful to not over-interpret any enhancement. With PoMELO Passive there is a relationship between sensitivity and false positives that is adjustable to context. In the operational context of PoMELO Passive, false positive detections are often considered expensive (similar to Barchyn et al., 2023), and the trade-off in terms of lower sensitivity is acceptable. This is an important conceptual caveat to detection sensitivity that extends beyond this study—if the operational context were different and false positives had a low penalty—PoMELO Passive would have much better detection sensitivity.

There was a loose relationship between release rate and detection (Figure 6) where there was some systematic partial detection at lower release rates (< 1 g/s). However, there were also missed detections at higher release rates. Imperfect detection, even at high emissions rates, can be caused by situations where the plume lofted and was missed by the vehicle. Similar effects from a drone were observed by Barchyn et al. (2017) and underscore that a 100% probability of detection is impossible when detection requires advection of the plume through the free atmosphere.

Further exploring detection (Figure 7), there was a clear relationship between wind speed and detection (Figure 7a) where missed detections were dominantly in situations with low wind speed and low release rate. This dependency is different than aerial systems, which tend to show decreased detection sensitivity with an increase in wind speed (Conrad et al., 2023). Some dependency with wind speed shows that a more enhanced prediction of detection capability is likely possible with consideration of environmental conditions. Further research is expected to produce a predictive model for detection like that of Thorpe et al. (2024).

Although it would be attractive to report a standardized rate-dependent probability of detection curve, both anecdotally and shown by Figure 7a, the presence of condition dependency means that there would be situations where such a number would seriously over- or under-estimate the detection capabilities of PoMELO Passive. Additionally, detection probability in Figure 6 links directly to the environmental conditions that occurred during tests. For example, there probably would be significantly fewer non-detections (and an artificial increase in measured detection sensitivity) if wind speeds were systematically higher (see Figure 4b). It is inadvisable to use the results in Figure 6 outside of the context of these tests.

There are contrasting and unclear reasons for the relations with conditions seen here. The results can be examined with some consideration of theory. Higher emissions rates should theoretically improve detectability as the concentration in the atmosphere increases proportional to release rate. This effect does match results in Figure 6 where detectability increases with emissions rate.

Less well explained is the inverse relationship with wind speed (Figure 7a). Low wind speeds increase the concentration in the air as there is less wind-induced dilution at the source, an effect that should increase the probability of detection (as seen by Conrad et al., 2023). However, with these experiments we are likely looking at a situation where the plume is lofting or missing the vehicle. It is possible that the real variable of interest is vertical atmospheric mixing.

Similarly unclear was the limited relation with downwind distance (Figure 7b). From theory, downwind distance should reduce methane concentration through increased lateral and vertical mixing, making detection less certain at further distances. This theoretical effect is not clearly observed. Downwind distance and wind speed may be interacting such that low wind speed conditions have a higher probability of plume lofting—but with increased downwind distance the plume vertically mixes back to the surface and the low detection probability at low wind speeds may only be an effect present at close distances. Further research will utilize additional variables not included in these data to better understand detection probability with PoMELO Passive, better proxy atmospheric conditions, and produce a model similar to Thorpe et al. (2024).

4.4 Quantification

4.4.1 Single-pass

Single-pass quantification results showed relatively unbiased results, and a linear model fit r^2 of 0.70 (Figure 8). These results primarily apply to the opportunistic sampling approach where a single pass are the only data available. It is likely that the subtle negative bias (0.927) was caused by the experimental conditions than a real bias. The algorithms in PoMELO Passive have been tuned to have no bias with a much larger internal dataset and we would hesitate to use the subtle bias reported here as an externally applied calibration when our internal dataset is much more robust. A possible future step is pooling all data to improve the bias calibration (c.f., Barchyn and Hugenholtz, 2022).

Variability is expected with single-pass measurements and results were similar to most other rapid methane measurement systems (see El Abbadi et al., 2024). In practice, this variability can be difficult to work with, but note that risk-based and Bayesian methods are now widespread and data analysis tooling for working with uncertain methane data is now common (see Wigle et al., 2024).

Only 70.9% of detections produced quantifications. This was a result of internal quality control criteria that limit quantifications in situations where data are unlikely to produce reasonable results. For example, situations where the plume was measured around a corner (see Figure 2) can cause issues with PoMELO Passive algorithms and are automatically excluded before even being calculated. No human judgement was made on a pass-by-pass basis with inclusion or exclusion criteria. The practical impact of this built-in selectivity is a reduction in data volume for opportunistic sampling, and potentially some extra passes required for targeted sampling missions.

Residuals showed little correspondence with release rate (Figure 9a). This is likely because most of the variability in predictions was caused by atmospheric behaviour (Caulton et al., 2018). Atmospheric behaviour is dominantly independent of release rate, and so long as concentration enhancements are above instrument noise and capable of being resolved by PoMELO Passive, there is little theory to support a dependence between release rate and residuals. This is a beneficial characteristic of the system because it suggests that larger releases (e.g., 'super-emitters') should have similar quantification error characteristics, and the relatively low release rates tested here should yield applicable results for larger releases outside of the test envelope.

Residuals did show some relation with wind speed (Figure 9d), with a systematic underprediction occurring with wind speeds below 3 m/s. This under-prediction could be due to issues where the plume mixed higher into the atmosphere than predicted, and only a relatively small amount of methane was on the surface, suggesting a lower emissions rate than reality. Although this issue has systematic internal corrections and is well known, results suggest that the corrections could be insufficient or not effectively capturing the exact environmental conditions that occurred during these tests. Broadly, low wind speeds (< 3 m/s) pose issues for both quantification and detection. Fortunately, these situations are relatively easy to identify and attach a note of caution.

Uncertainty predictions were slightly more conservative than necessary, suggesting that PoMELO Passive slightly overpredicts uncertainty and is more accurate than predicted. Although it would be preferable to predict uncertainty perfectly, overprediction of uncertainty is often more desirable than underprediction for many applications with PoMELO Passive.

4.4.2 Multi-pass

Multi-pass quantification results had little variability when pooled among all available replicates (Figure 10). Generally, this suggests that PoMELO Passive is much more accurate when pass-to-pass variability is averaged out. Accuracy improvements with averaging also suggest that much of the single-pass variability could be caused by turbulent structures in the atmosphere, which is similar to the results presented by Caulton et al. (2018).

Results by Caulton et al. (2018) mirror improvements in accuracy with increasing n seen in these results (Table 3). Caulton et al. (2018) recommended n = 10 as an effective number of passes through detailed empirical and simulation study. Although the algorithms used by PoMELO Passive are different than the

Gaussian models used by Caulton et al. (2018), 10 passes would indeed yield high quality results with PoMELO Passive. We do not specify an optimal *n* here as the operational penalties associated with performing large number of passes tend to be application specific.

Replicate releases were not systematically conducted on the same day (or in the same conditions, Figure 5a). This has several implications when considering the operational use case of targeted sampling. First, observations on many different days reduce the impact of certain conditions biasing the results. Targeted sampling is likely to be performed on one day, with pa0sses completed in short succession, which could result in some condition-based bias. Second, a minute-scale wait time between passes was shown to be important by Caulton et al. (2018) as it ensures that large eddy structures are not sampled repeatedly. This was inherently achieved in these tests, but if this is an effect that should be translated into a guideline for targeted repeat sampling, the wait time between passes may be the limiting factor on sampling efficiency.

Broadly though, quantification results with repeat sampling are class-leading, exceeding the accuracy of many airborne technologies (El Abbadi et al., 2024), and satellite technologies (Sherwin et al., 2024) – suggesting that high quality, unbiased results are possible using relatively inexpensive equipment on the ground.

Targeted sampling campaigns need to plan to perform extra passes. As only 70.9% of detections produced quantifications (due to internal quality control criteria), an oversample fraction of 1.41 should be considered if a certain number of passes are required to hit a target accuracy and mitigate the potential of failing to produce a sufficient number of data points. Note that experienced operators of PoMELO quickly learn the issues which cause quality control failures as PoMELO Passive provides explanations of all quality control issues.

An important caveat of these results is that we do not combine emissions estimates using Bayesian methods, which would both (i) be more accurate than averaging, and (ii) effectively predict the aggregated uncertainty. This was impossible within these single-blind tests as we would need to know which releases were replicates before reporting results. Real application of PoMELO Passive for targeted repeat sampling would not have this limitation and would inherently produce more accurate results with Bayesian uncertainty estimates (see Wigle et al., 2024).

5 Conclusions and applicability

The PoMELO Passive system has demonstrable capabilities to both detect and quantify emissions in opportunistic or directed sampling programs. A major pan-Canadian opportunistic methane measurement program is built around PoMELO Passive, indicating that the strategy of operational opportunistic sampling from vehicle-based systems is a scalable, low-cost, and effective approach to understand emissions from upstream oil and gas sites.

The PoMELO Passive technology is highly applicable to the upstream oil and gas industry, where a transition in both understanding methane emissions and measurement capability is occurring. There is a diversity of emissions measurement technologies that can measure ‘super-emitters’ (see Vollrath et al., 2024)—but emerging research indicates that smaller sites are a bigger proportion of emissions than previously thought. For example, Williams et al. (2025) indicate that 70% of emissions in the continental U.S. originate from sites with emissions rates less than 27.8 g/s, and 30% originate from sites with emissions rates less than 2.8 g/s (also see references cited within Williams et al., 2025). This indicates that there is significant need for measurement technologies that measure rates similar to those tested here.

PoMELO Passive is well suited to meet this need with strong detection performance > 1 g/s and robust quantification capabilities. This measurement technology is critical to avoid extrapolation and assumptions regarding sites below the detection limit of satellites and aircraft.

6 Acknowledgements

We thank the AMEP program for study funding (see www.amep.ca). We thank Adam Hayman and Negar Nazari for fieldwork, releases, and data analysis. We thank Michael Nightingale for gas analysis. We thank Parry Manning for field assistance. We thank Zhenyu Xing for comments on a previous version of this manuscript and helpful discussion.

7 References

Barchyn, T.E., 2025. PoMELO Passive AMEP Blind Test Results. Available at: https://doi.org/10.5683/SP3/S88VME (accessed 18 February 2025).

Barchyn, T.E., Hugenholtz, C.H., Myshak, S., Bauer, J., 2017. A UAV-based system for detecting natural gas leaks. Journal of Unmanned Vehicle Systems 6, 18-30. Doi: doi.org/10.1139/juvs-2017-0018.

Barchyn, T.E., Hugenholtz, C.H., 2020. University of Calgary Rapid Vehicle-based Methane Emissions Mapping System (PoMELO) Single-Blind Testing Results from the Methane Emissions Technology Evaluation Center (METEC). Available at: https://www.ucalgary.ca/live-uc-ucalgary-site/sites/default/files/teams/441/UCalgary_PoMELO_METEC_Detection_2020.pdf (accessed 06 January 2025).

Barchyn, T.E., Hugenholtz, C.H., 2022. Complex multi-source emissions quantification results for the PoMELO vehicle measurement system, test results from the CSU METEC facility. Earth ArXiv Preprint. Doi: doi.org/10.31223/X5XP7B.

Barchyn, T.E., Hugenholtz, C.H., Gough, T., Vollrath, C., Gao, M., 2023. Low-cost fixed sensor deployments for leak detection in North American upstream oil and gas: Operational analysis and discussion of a prototypical program. Elementa: Science of the Anthropocene 11, 00045. Doi: doi.org/10.1525/elementa.2023.00045.

Billinghurst, C.D., 2024. Open or closed? Measurement performance of open- and closed-path methane sensors for mobile emissions screening. Master's thesis, University of Calgary, Calgary, Canada. Available at https://hdl.handle.net/1880/117930 (accessed 06 January 2025).

Caulton, D.R., Li, Q., Bou-Zeid, E., Fitts, J., Golston, L.M., Pan, D., Lu, J., Lane, H.M., Buchholz, B., Guo, X., McSpiritt, J., Wendt, L., Zondlo, M.A., 2018. Quantifying uncertainties from mobile-laboratory-derived emissions of well pads using inverse Gaussian methods. Atmospheric Chemistry and Physics 18, 15145-15168. Doi: doi.org/10.5194/acp-18-15145-2018.

Conrad, B.M., Tyner, D.R., Johnson, M.R., 2023. Robust probabilities of detection and quantification uncertainty for aerial methane detection: Examples for three airborne technologies. Remote Sensing of Environment 288, 113499. Doi: doi.org/ 10.1016/j.rse.2023.113499.

El Abbadi, S.H., Chen, Z., Burdeau, P.M., Rutherford, J.S., Chen, Y., Zhang, Z., Sherwin, E.D., Brandt, A.R., 2024. Technological maturity of aircraft-based methane sensing for greenhouse gas mitigation. Environmental Science & Technology 58, 9591-9600. Doi: doi.org/10.1021/acs.est.4c02439.

Fox, T.A., Barchyn, T.E., Risk, D., Ravikumar, A.P., Hugenholtz, C.H., 2019. A review of close-range and screening technologies for mitigating fugitive methane emissions in upstream oil and gas. Environmental Research Letters 14, 053002. Doi: doi.org/ 10.1088/1748-9326/ab0cc3.

Gao, M., Hugenholtz, C.H., Barchyn, T.E., 2022. Development and validation of a route planning methodology for vehicle-based remote measurements of methane and other emissions from oil and gas wells and facilities. Journal of the Air & Waste Management Association 72, 1279-1289. Doi: doi.org/10.1080/10962247.2022.2113182.

Gao, M., Xing, Z., Vollrath, C., Hugenholtz, C.H., Barchyn, T.E., 2023. Global observational coverage of onshore oil and gas methane sources with TROPOMI. Scientific Reports 13, 16759. Doi: doi.org/10.1038/s41598-023-41914-8.

Ilonze, C., Emerson, E., Duggan, A., Zimmerle, D., 2024. Assessing the progress of the performance of continuous monitoring solutions under single-blind controlled testing protocol. ChemRxiv Preprint. Available at: https://chemrxiv.org/engage/chemrxiv/article-details/65c2903e66c1381729198ee8 (accessed 06 January 2025).

Ilonze, C., Day, R., Emerson, E., Duggan, A., Brouwer, R., Zimmerle, D., 2025. Performance of survey solutions under single-blind controlled testing protocol. ChemRxiv Preprint. Available at: https://chemrxiv.org/engage/chemrxiv/article-details/6773e1dffa469535b95ae17e (accessed 06 January 2025).

Sherwin, E.D., El Abbadi, S.H., Burdeau, P.M., Zhang, Z., Chen, Z., Rutherford, J.S., Chen, Y., Brandt, A.R., 2024. Single-blind test of nine methane-sensing satellite systems from three continents. Atmospheric Measurement Techniques 17, 765-782. Doi: doi.org/10.5194/amt-17-765-2024.

Thorpe, M.J., Kreitinger, A., Altamura, D.T., Dudiak, C.D., Conrad, B.M., Tyner, D.R., Johnson, M.R., Brasseur, J.K., Roos, P.A., Kunkel, W.M., Carre-Burritt, A., Abate, J., Price, T., Yaralian, D., Kennedy, B., Newton, E., Rodriguez, E., Ibrahim Elfar, O., Zimmerle, D.J., 2024. Deployment-invariant probability of detection characterization for aerial LiDAR methane detection. Remote Sensing of Environment 315: 114435. Doi: doi.org/10.1016/j.rse.2024.114435.

Vollrath, C., Hugenholtz, C.H., Barchyn, T.E., 2024. Onshore methane emissions measurement from the oil and gas industry: a scoping review. Environmental Research Communications 6, 032001. Doi: doi.org/10.1088/2515-7620/ad3129.

Wigle, A., Béliveau, A., Blackmore, D., Lapeyre, P., Osadetz, K., Lemieux, C., Daun, K., 2024. Estimation and applications of uncertainty in methane emissions quantification technologies: A Bayesian approach. ACS EST Air 1, 1000-1014. Doi: doi.org/10.1021/acsestair.4c00030.

Williams, J.P., Omara, M., Himmelberger, A., Zavala-Araiza, D., MacKay, K., Benmergui, J., Sargent, M., Wofsy, S.C., Hamburg, S.P., Gautam, R., 2025. Small emission sources in aggregate disproportionately account for a large majority of total methane emissions from the US oil and gas sector. Atmospheric Chemistry and Physics 25, 1513-1532. Doi: doi.org//10.5194/acp-25-1513-2025.