Field Performance of New Methane Detection Technologies: Results from the Alberta Methane Field Challenge

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Abstract

Emerging methane technologies promise rapid and cost-effective methods to measure and monitor methane emissions. Here, we present results from the Alberta Methane Field Challenge – the first large-scale, concurrent field trial of eleven alternative methane emissions detection and quantification technologies at operating oil and gas sites. We evaluate the new technologies by comparing their performance with conventional optical gas imaging survey. Overall, technologies are effective at detecting methane emissions, with 8 out of 11 technologies achieving an effectiveness of approximately 80%. Importantly, results highlight the key differences in technology performance between those observed at controlled release tests versus those in field conditions. Intermittent emissions from tanks substantially affects detection and site-level quantification estimates and should be independently monitored while assessing technology performance. In this study, all technologies improved their effectiveness in detecting tank emissions when intermittency was considered. Truck- and plane-based systems have clear advantages in survey speed over other technologies, but for some their ability as effective screening technologies to identify high-emitting sites rests on their quantification effectiveness. Drone-based technologies demonstrated higher effectiveness than other technologies in identifying quantification rank compared to baseline OGI-based survey. Overall, quantification under in-field conditions is affected by several exogenous factors such as temporal variation in emissions and changing environmental conditions. We recommend that assessment studies of new methane detection technologies at oil and gas facilities include comprehensive, continuous, and redundant emissions estimates.

Keywords: Methane Emissions; Methane Policy; Leak Detection and Repair; Methane Policy; Optical Gas Imaging

1. Introduction

Methane emissions across the oil and gas supply chain erode the potential climate benefits of using natural gas over other carbon-intensive fuels such as coal [1]. The Intergovernmental Panel on Climate Change (IPCC) in its recent report on 1.5°C of global warming highlighted the importance of reducing short-lived greenhouse gases such as methane [2]. Methane, the major component of natural gas, has a significantly higher global warming potential than carbon dioxide. Recent research has shown that despite their short atmospheric lifetime, methane emissions can contribute to decades of future sea-level rise [3]. Locally, reducing methane emissions also reduces emissions of volatile organic compounds from oil and gas operations and improves air quality [4]. Beyond these local and global impacts, several recent field campaigns to measure methane emissions have demonstrated a consistent underestimation in official GHG inventories [5]–[8]. These discrepancies further underscore the need for effective monitoring and mitigation of oil and gas methane emissions. Effective mitigation can also save money, where 'leaked' methane from fossil fuel operations can be sold to customers or used as on-site fuel [9].

The United States (US), Canada, and Mexico committed to reducing their methane emissions from the Oil and Gas sector as part of the North American Climate, Clean Energy, and Environment Partnership Action Plan [10]. Subsequently, US states such as Colorado and California, and provincial and federal governments in Canada have implemented leak detection and repair (LDAR) programs as part of efforts to reduce emissions from upstream oil and gas activities [11]–[14]. Typically, LDAR surveys are conducted using two commonly used technologies: US Environmental Protection Agency (EPA) Method-21 and optical gas imaging (OGI) systems. While recent studies have found OGI-based LDAR surveys effective in detecting and reducing emissions, they are time-consuming and expensive [10], [15]. OGI-based surveys involve a 2-person crew covering 4 – 6 well sites per day, which does not scale effectively across thousands of geographically sparse well sites. This makes frequent monitoring challenging even as other studies point to the need to quickly find and repair stochastic, high-emitting leaks [16]–[18].

Recently, several new methane emissions detection technologies that promise faster and more cost-effective leak detection than existing approaches have been developed [19]. These technologies include continuous monitoring systems, mobile sensors mounted on drones, trucks, and planes, handheld sensors, and satellite systems [20]. Most of these technologies are not currently approved for use in regulatory LDAR programs. To enable widespread deployment, the efficacy of new technologies must be validated through rigorous testing, modeling, and field trials.

Recent studies in the US have evaluated a variety of mobile methane detection technologies under controlled conditions [21]–[23]. The Stanford/EDF Mobile Monitoring Challenge, for example, evaluated ten truck-, drone-, and plane-based systems for their effectiveness in detecting and quantifying methane emissions at controlled release test facilities [21]. The US Department of Energy's MONITOR program funded the development of several new methane sensors that were tested under controlled conditions [24]. While these studies provided data on technology parameters such as probability of detection and false positive rates, they are not representative of typical oil and gas operations. Thus, systematic field trials at producing oil and gas sites are critical to understanding real-world performance of new technologies in detecting and quantifying methane emissions.

Field studies have been conducted as part of recent methane measurements campaigns. Mobile truck-based platforms were deployed in British Columbia and Alberta to measure site-level emissions, while plane-based systems were used to detect site- and basin-level emissions in the US [25]–[31]. More recently, scientists deployed drone-based systems for methane detection and quantification at oil and gas facilities [29], [30], [32]. Finally, satellites have been used to study regional and global methane emissions from anthropogenic and biogenic sources, and to identify high-emitting methane sources associated with oil and gas activity [33]–[40]. However, despite the use of alternative technologies in scientific studies for measuring methane emissions from oil and gas operations, there has been no systematic field test of their performance.

In this paper, we report results from the Alberta Methane Field Challenge (AMFC) – the first large-scale, concurrent field trial of alternative methane emissions detection and quantification technologies at operating oil and gas sites. We tested twelve different technology teams, including fixed continuous monitoring systems, handheld devices, and truck-mounted, drone-mounted, and plane-based systems across 55 upstream oil and gas production facilities near Rocky Mountain House, Alberta. The AMFC provides a scientific understanding of the performance of methane emissions detection/quantification technologies under varying field conditions. Critically, our study demonstrates the challenges of evaluating 'snapshot' measurement technologies under spatially and temporally varying methane emissions. We conclude with recommendations on future field testing that can enable a robust performance comparison of new methane detection systems with existing regulatory approaches.

2. Study Design & Methodology

2.1 Technology Team Selection

AMFC participants were selected through a rigorous application process that included an application, evaluation of technology platforms, and an invitation to participate (Supplementary Information [SI] Section 1). Participants were selected based on their technological capabilities, prior testing experience, and deployment and scalability. In addition, the number of teams using a specific platform (e.g., drone, truck, plane etc.) were also limited by the logistics of organizing a safe, large-scale, blind, and concurrent field campaign. In all, 40 technologies applied to participate, of which 12 were selected. A summary of the participating technology teams (hereafter referred to as teams) is given in Table 1. The AMFC campaign was held in two phases – phase 1 and 2 – with truck teams participating in both. Detailed technical specification about each participating team is provided in SI section 2. The fixed sensor analysis is included in SI section S3 and not in the main text due to the nature of analysis required as compared to other teams which participated in the AMFC. The Heath team did not report quantified emissions rates or emissions attribution, and the analysis in the SI has been conducted by the authors of this paper.

Table 1: Summary of technology platform, sensor type, and level of detection for each participating team in the AMFC.

Technology Teams	Platform	AMFC Phase	Sensor Type	Detection Resolution
Altus Geomatics (now GeoVerra)	Truck	1 & 2	Cavity ring-down spectroscopy	Site
University of Calgary (UofC)	Truck	1 & 2	Open-path wavelength modulated spectroscopy	Equipment & Site
Aerometrix Inc.	Drone	1	Tunable open-path laser absorption spectroscopy	Equipment
SeekOps Inc.	Drone	1	Miniature methane tunable laser absorption spectroscopy	Equipment
Bridger Photonics	Plane	1	Spatially scanned airborne LiDAR	Equipment & Site
Sander Geophysics Ltd.	Plane	2	Off-axis integrated cavity output spectroscopy	Site
Tecvalco Ltd.	Hand-held	2	Tunable diode laser absorption spectroscopy	Component
FLIR Systems	Hand-held	2	Uncooled infrared camera	Component
Heath Consultants Inc.	Hybrid (truck and handheld)	1	Open-path etalon spectroscopy and backscatter tunable diode laser absorption spectroscopy	Component & Site
Heath Consultants Inc.	Fixed	1	Long open-path backscatter tunable diode laser absorption spectroscopy	Equipment & Site

2.2 Test Location

The AMFC phase 1 and phase 2 campaigns were conducted between June 11-21, 2019 and November 14-24, 2019, respectively, across 55 upstream oil and gas facilities near Rocky Mountain House, Alberta. These sites were selected based on ease of access, surrounding vegetation type (forested vs. prairie), site-size, and representativeness to assets in the larger production region. Each AMFC phase included measurements at approximately 50 sites, of which 45 overlapped between the two phases. Phase 2 also included a controlled release test set-up to evaluate the quantification accuracy of participating teams. Details on organizing the field campaign, field scheduling, in-field communications, and data integrity and handling procedures can be found in supplementary information – these are provided to assist in the development and execution of future field campaigns (SI section 1).

2.3 Baseline Data Collection

Davis Safety Consulting Inc. ('OGI crew') was selected to collect baseline methane emissions data using OGI technology based on prior participation and experience in collecting research-quality data [15]. The OGI crew used a FLIR Technologies' GF-320 infrared camera for emissions detection and the Providence Photonics QL-320 quantitative optical gas imaging (QOGI) instrument for emissions quantification. The QOGI operates by identifying the methane plume pixels on the OGI camera and calculating the effective absorption cross section at each pixel [41]. The baseline data collection included both leaks and vents, and an indication of the temporal nature of the emission (continuous vs. intermittent). The QOGI was selected for emissions quantification over the conventional Bacharach Hi-Flow sampler because of its ability to comprehensively quantify all emissions. The Hi-Flow sampler, on the other hand, can only be used to measure leaks that are accessible and safe and therefore often excludes high emitting sources such as tanks [42]. Furthermore, the maximum flow rate that can be measured with the Hi-Flow sample is 630 standard cubic feet per hour (scfh) [43, p. 8] and large emitters can have significantly higher emission rates [31], [43]–[45]. The quantification accuracy of the QOGI was evaluated through single-blind controlled release measurements (Section 3). Two crews were deployed throughout the AMFC program to increase baseline survey speed. Each day, the OGI crews visited a pre-selected list of 3-5 'mandatory' sites which the participating teams were also required to visit on the same day to minimize temporal mismatch (SI section 1.2). Sites visited by both the participating team and OGI crew on the same day are referred as "overlap sites". In addition, teams could also measure emissions from non-mandatory sites after measurements at mandatory sites were completed.

2.4 Performance Metrics

Technologies were assessed on their effectiveness in emissions detection, localization, and quantification as compared to the OGI baseline. In addition, we also analyzed deployment metrics such as survey speed and measurement time relevant in field settings.

Site-level detection effectiveness: The detection effectiveness is defined as the percentage of overlap sites which were identically detected by the participating teams and the baseline OGI survey. This metric only considers site-level binary emissions detection and does not differentiate between the number of sources found within a site for teams that identify equipment-level emissions. Any non-zero emission detected by a team at a given site is given a value of 1 while sites with no detected emissions is 0. There are two possible outcomes: one, same detection as OGI which includes scenarios where OGI and the team agree on site-level emissions indication (OGI = 1, team =1; and OGI = 0, team = 0); and two, different detection from OGI which includes scenarios where OGI and the team diverge on site-level emissions indication (OGI = 1, team = 0; and OGI = 0, team = 1). Mismatch in performance can arise from several factors impacting both OGI and the teams including technology limitations, site configuration, temporal variability in emissions, or weather-related changes to detection thresholds. Moreover, this analysis is distinct from conventional definitions of true positive or true negative measurements employed in controlled release experiments because OGI detections do not necessarily represent the ground truth [21].

Equipment-level detection: For teams that detect equipment-level emissions, effectiveness is defined as the fraction of overlap sites at which a participating team detected emissions across five major equipment categories as compared to the baseline OGI survey: buildings, compressors, wellheads/pumpjacks, separator/dehydrator, and tanks. Equipment descriptions provided by the participating teams that did not fit into any of these categories were grouped under 'other'. As before, this analysis only considers binary emissions detection for each equipment and not individual instances of emissions for a given equipment type. For example, detection of emissions from two tanks or three tanks from the same site are treated equally as an emissions detection from tanks. This simplification is necessary to resolve ambiguities in equipment descriptions as reported by individual teams and OGI. Because major equipment on site can be enclosed in buildings, we consider emissions detection from a building by a team as a proxy for emissions from the equipment inside the building as identified by OGI. This assumption was also applied to separator/dehydrator and compressors.

Site-level Emissions Quantification Accuracy: Quantification accuracy is shown as a parity chart of rank-ordered emissions by OGI and the participating teams at overlap sites. Here, accuracy is defined as the number of overlap sites ranked within 20% of OGI ranks. This metric has been aggregated at the site-level for teams that measure equipment-level emissions. Consequently, site-level aggregation of participating teams may not include all the emissions identified at the site by the OGI team. In this case, differences in quantification can arise from errors in quantification, ‘missed’ equipment-level detections, or temporal variation in emissions. Parity charts of site-level quantification accuracy between teams and baseline OGI survey are provided in SI section 6.

3. Quantification Accuracy of QOGI

Here, we report on results from the controlled release test of the Providence Photonics’ QL-320 quantitative optical gas imaging (QOGI) instrument during the AMFC phase 2 campaign. The controlled release tests were conducted on a non-operating oil and gas site that was verified to not have any residual methane emissions but was still subject to similar environmental conditions as operating sites. The releases were roughly equally split between two release heights – 5 ft and 15 ft (SI section 4.1). Across the 11 days of the AMFC phase-2 campaign, each of the two OGI crews took part in approximately 50 controlled releases ranging from about 30 scfh to 1900 scfh. The emissions rates were chosen not to evaluate the detection threshold for the OGI camera but to test quantification accuracy of QOGI across the range of emissions typically observed at oil and gas facilities. For more details on experimental set-up and uncertainty analysis of the QOGI performance, refer to SI section 4.

Figure 1 (a) shows the parity chart of controlled release tests for the QOGI across both measurement heights and OGI crews. A least-squares linear regression coefficient of 0.82 was observed (R^2 = 0.6, 95% confidence interval [0.73, 0.92]), thus demonstrating reasonable effectiveness in estimating aggregate emissions rates. For tests below 1000 scfh, the slope of linear regression is measured to be 0.86, with a 95% confidence interval between 0.72 and 1. The aggregate error in quantification from controlled release tests is 18% across the range of release rates, comparable to that of the Bacharach Hi-Flow sampler (~10%) [43]. This aggregate error rate will change depending on the number of emissions per site, where it will be larger for sites with fewer emissions. Figure 1 (b) shows the parity chart of emission rank for the true release rates and the QOGI estimated rates, ranked largest to smallest. The QOGI instrument was 72% effective in estimating emission rank within 20% of the rank of the true release rates.

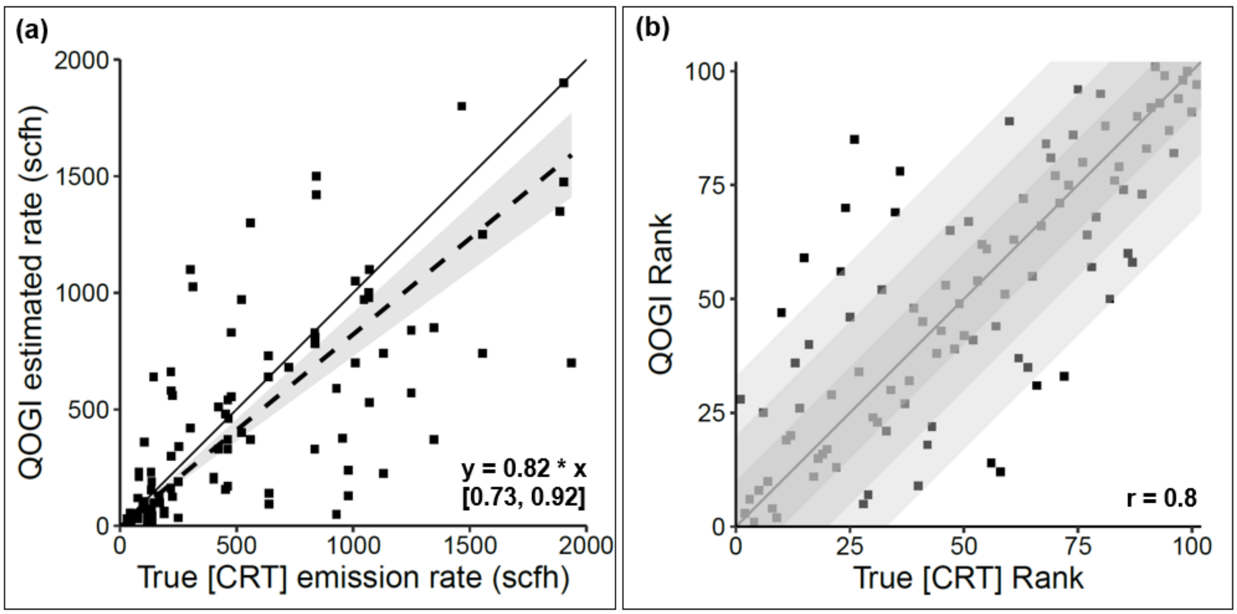

Figure 1: (a) parity chart of controlled release tests for QOGI across both measurement heights (5 feet and 15 feet) and the two OGI crews. (b) Parity chart of quantification rank between OGI and true CRT rank. The largest emission is given a rank of 1. The black reference line shows a 1:1 relationship where OGI rank = CRT rank and has a slope=1. The gray shaded region shows OGI ranked emissions within 10% (darkest), 20%, and 33% (lightest) of CRT ranks.

To further improve our understanding of measurement uncertainty in QOGI-based quantification estimates, we use Monte-Carlo analysis to estimate error as a function of sample size (SI section 4.1). Using a bootstrapped sampling technique (with replacement) and 10000 Monte-Carlo realizations, we find that the 5th and 95th percentile of the sample mean are -23% and +26%, respectively, for a sample size of 50 (SI Figure S7). Similarly, at a sample size of 20 emissions – typically seen in production sites – the 95% confidence bounds of the average emission rate is -

34% and +39%. Thus, it is critical for QOGI measurements to be interpreted in an aggregate context, as individual measurements can have higher error rates as shown in Figure 1(a). Nevertheless, the critical advantage of being able to estimate all methane emissions at a site outweighs the higher error in QOGI-based quantification. Detailed analysis showing the variation of quantification effectiveness with release height (SI Figure S4) and thermographer operation (SI Figure S5) are available in the supplementary information. Even as this study provides the first large-scale, independent verification of the quantification accuracy of the QOGI instrument, future work is critical to improve our understanding of the precision of the instrument under realistic equipment configurations - different orifice sizes, backgrounds, weather conditions, and gas compositions.

4. Results

In this section we present results from both phases of the AMFC. A few caveats will help in interpreting results.

1. Many of the participating teams are early-stage technology companies (technology readiness levels 4 – 7) and the results reported here are likely not representative of their most up-to-date performance.
2. Because of the inherent uncertainty in detecting methane emissions at operating oil and gas facilities, the results reported here do not represent the ground truth performance of participating teams but rather a relative comparison with OGI-based leak detection surveys. Determining technology-specific parameters such as leak detection threshold will require detailed controlled release experiments similar to the Mobile Monitoring Challenge [21].

3. Several prior studies emphasize the importance of temporal variation in methane emissions [5], [7], [31], [46]–[48]. Differences in performance between teams and baseline OGI data likely arise from a combination of technology performance limitations, intra-day changes in methane emissions, variation in environmental conditions, or other factors such as downwind access to emitting equipment.

4.1 Site-level Emissions Detection

Table 2 shows a summary of the site-level performance of the participating teams. The comparison with baseline OGI survey is only made at overlap sites, which is limited by the survey speed of the OGI team (3-6 sites/day). We make several important observations.

First, seven out of eleven teams demonstrate high effectiveness (approximately 80%) in detecting site-level methane emissions compared to the baseline OGI survey. Laser-based technologies tend to have higher sensitivity compared to imaging-based sensors such as OGI cameras and therefore emissions that are detected by OGI tend to also be detected by other laser-based technologies. In particular, SeekOps (drone), Aerometrix (drone), and Heath (hybrid), found emissions at a site where OGI did not. These emissions were found on tanks that were either likely not in the line-of-sight for a ground based OGI crew, or they could be intermittent in nature and thus not emitting when OGI was on site. The low detection effectiveness of FLIR Systems can be attributed to the lower sensitivity of uncooled infrared imaging systems compared to the baseline OGI survey that used cooled infrared detectors. The detection effectiveness of plane-based systems varied based on the metric chosen. In the case of Bridger Photonics, only ‘tier-1’ emissions - where the technology was able to localize and quantify methane plumes were considered, leading to a 43% detection effectiveness. In addition, Bridger also identified ‘tier-3’ emissions that correspond to plumes that were observed but too weak to localize or quantify. Including these ‘tier-3’ emissions, the detection effectiveness increased to 90%. However, ‘tier-3’ emissions detections cannot be used for follow-up emissions mitigation action as the weak plumes could not be localized. Similarly, although Sander Geophysics’ detected emissions at 77% sites found by the OGI crew, they were only able to quantify emissions from four sites because of unstable wind conditions. These results suggest that effectiveness of plane-based technologies can vary based on whether the primary application is emissions detection or quantification.

Second, survey speed varied from 3 sites/day for Tecvalco to 15 sites/day for Altus Geomatics, indicative of the range of survey methods employed. On average, aerial and truck-based systems that measure at the site-level are at least three to five times faster than the baseline OGI survey. For all technologies, survey speeds as part of an LDAR program deployment can be expected to be somewhat higher than those observed in this study because of artificial constraints that restricted survey speed. For example, not all sites in the region were measured in the AMFC campaign and so a greater fraction of time was spent traveling between sites. Furthermore, the need to wait for a prior team to finish measurements if teams ended up on a site concurrently further reduced survey speed. The aerial teams (drones and planes) flew only for 2 – 4 hours per day and thus their survey speed is lower than what should be expected if they flew more hours per day. The lower average survey speed for truck-based systems in the phase 2 campaign compared to the phase 1 campaign can be attributed to the addition of controlled release testing, winter driving conditions, and shorter daylight hours in November.

Table 2: Site-level performance for participating teams in the Alberta Methane Field Challenge (AMFC) as compared to baseline OGI survey. Effectiveness (%), in bold, is the percentage of overlap sites which were identically detected by the participating teams and OGI.

Tech. Team	Type	AMFC Phase	No. of days	Total sites visited	Overlap sites	Survey speed (sites /day)	Survey time (min /site)	Effective-ness (%)	Same as OGI		Diff. from OGI	
									OGI=1, Team=1	OGI=0, Team=0	OGI=0, Team=1	OGI=1, Team=0
Aerometrix Inc.	Drone	1	10	42	29	5	20	**79%**	23	0	2	4
SeekOps Inc.	Drone	1	11	54	38	5	36	**92%**	35	0	1	2
Bridger Photonics*	Plane	1	5	65	20	13	7	**40%**	6	2	0	12
Sander Geophysics**	Plane	2	7	39	30	6	23	**77%**	23	0	1	6
Tecvalco ltd.	Hand.	2	5	10	9	3	52	**89%**	8	0	0	1
FLIR Systems	Hand.	2	5	26	24	5	36	**29%**	5	2	0	17
Heath Consultants	Hybrid	1	11	53	45	5	41	**91%**	41	0	4	0
Altus Geomatics (now GeoVerra)	Truck	1	10	127	40	15	9	**88%**	33	2	0	5
Altus Geomatics (now GeoVerra)	Truck	2	11	90	47	8	5	**94%**	43	1	1	2
Univ. of Calgary (UofC)	Truck	1	11	90	47	8	10	**81%**	36	2	2	7
Univ. of Calgary (UofC)	Truck	2	11	54	41	5	6	**90%**	36	1	1	3

* Only 'tier-1' emissions where the technology was able to localize and quantify methane plumes were considered. Bridger Photonics also identified 'tier-3' emissions that correspond to plumes that were observed but too weak to localize or quantify. Including these 'tier-3' emissions, the detection effectiveness increases to 90%. However, 'tier-3' emissions detections cannot be used for follow-up emissions mitigation action as the weak plumes could not be localized.

** Sander only reported and quantified 4 emissions of which 2 overlap with OGI which leads to an effectiveness of 16%. The 77% effectiveness is based on all detections made by Sander Geophysics irrespective of their ability to quantify those detections. Sites where emissions could not be resolved from other sources have not been included, similar to Bridger's 'tier 3' emissions.

Third, measurement time varied between under 10 minutes per site for Bridger, UofC, and Altus to over 30 minutes per site for other teams. For comparison, the baseline OGI survey took an average of 76 minutes per site, as per the design of the field campaign. The average measurement time for handheld teams is between 30 and 60 minutes per site, with the variation depending on quantification protocols for the team. However, handheld and hybrid (Heath) teams provided actionable information for component-specific repair, unlike other equipment- or site-level technologies, and should be considered in context of their application. In general, truck- and plane-based teams were faster than the baseline OGI survey. Both truck teams had similar survey times but varied in survey speed. These differences can be partly attributed to differing survey methodologies and additional time to collect ancillary data such as site layout by the UofC team, or partly may arise because Altus is commercial service provider and UofC is a research institution. Differences in time spent on site between Bridger (7 min/site) and Sander (23 min/site) can be attributed to Sander surveying sites by flying loop patterns around each site compared to Bridger conducting two to four passes over the site. This difference in survey methodology, in turn, may be a function of the different survey methodology or the sensor technologies deployed – Bridger's technology is based on hyperspectral imaging while Sanders' is based on direct measurements of methane concentration. Measurement time notwithstanding, all teams that measured emissions at the equipment- or site-level will require secondary inspection for repair. The time required for secondary, component-level inspection is not included in this analysis.

Based on comparisons with site-level baseline OGI survey emissions quantification, we find that most teams show a clear differentiation between sites that were identically detected with OGI and sites that were not. Figure 2 shows the average site-level emissions quantification estimated by the baseline OGI survey at overlap sites, comparing identically detected sites (same as OGI) with where a divergence between OGI and the team was observed (different from OGI). It is important to not interpret these differences as indicative of detection thresholds of the technologies, which are evaluated through controlled releases tests. The data here highlight important differences in technology performance between those observed at controlled release tests versus those at producing oil and gas facilities.

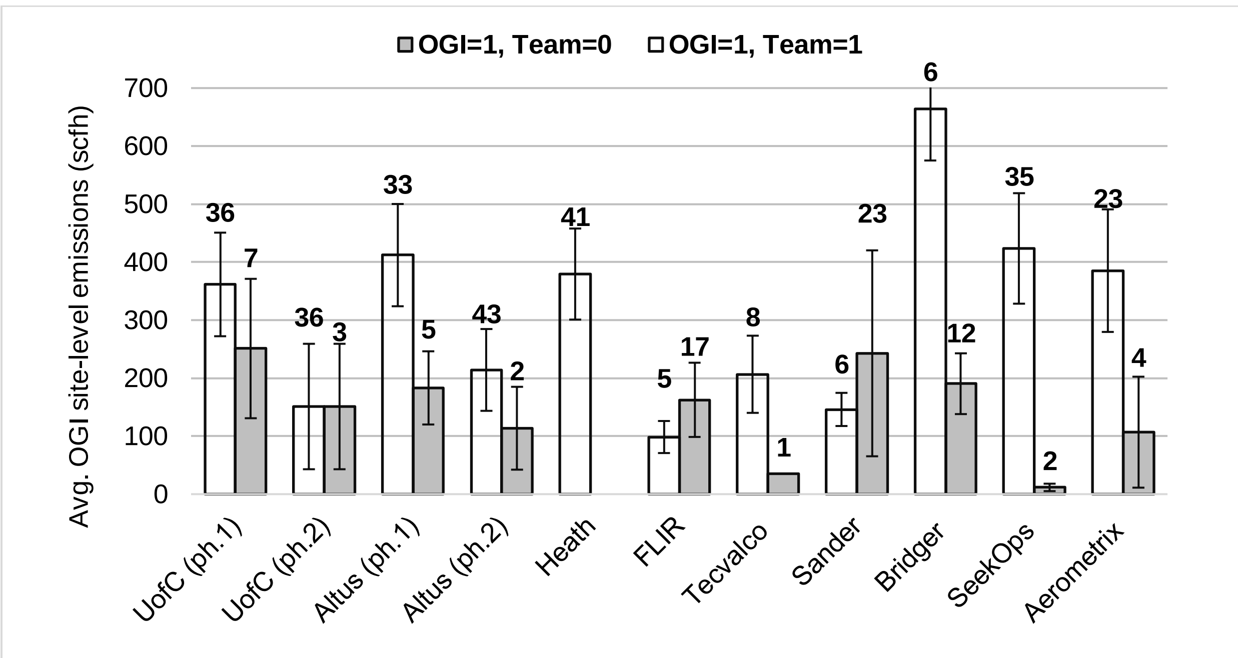

Figure 2: Average site-level emissions (scfh) estimated by QOGI at overlap sites where teams and QOGI both detected emissions (black outline), and where teams failed to detect but QOGI made a detection (-grey bars). Error bars represent one standard error from the mean. Numbers represent sample size for emissions calculation. Data is for sites where OGI = 1, team = 1 (same as OGI), and for OGI=1, team = 0 (different from OGI).

For most participating teams, the average baseline OGI site-level emissions rates were higher at sites where the teams' detection was identical to that of OGI, compared to where they diverged. For example, the average site-level emission estimated by QOGI at sites that SeekOps identically detected with OGI is about 420 scfh, while the average emissions at sites where SeekOps did not detect emissions found by the OGI crew is 20 scfh. However, UofC (both phases) and Altus (phase 1) do not show a significant divergence in average emissions rates between similar and different OGI detections.

4.2 Equipment-level Emissions Detection

Table 3 shows the detection effectiveness across five major equipment types at overlap sites for teams that detected equipment level emissions. We make several observations.

First, the drone and truck teams designed to detect equipment-level emissions (SeekOps, Aerometrix, UofC, Heath) demonstrated effectiveness over 65% in detecting the correct emitting equipment category compared to baseline OGI survey. While SeekOps was 81% effective, Aerometrix had an overall effectiveness of 70%. However, Aerometrix reported several emitting equipment sources as plausible source locations for each emission, thus, significantly reducing the localization effectiveness for future repairs.

Second, teams exhibit significant variation in detection effectiveness across equipment types. Both the drone teams demonstrated over 67% effectiveness in detecting tank emissions. In comparison, the UofC truck-based team demonstrated 32% and 55% effectiveness in identifying tank-related emission in the two phases of the AMFC campaign. However, across all equipment categories, the UofC team was very effective, detecting at least 67% of emissions identified by the baseline OGI survey. Unstable atmospheric conditions can impact sampling methods for trucks such as plume lofting and gaining downwind access to major equipment. This difference between tanks and other equipment types suggests further testing for truck-based teams to identify potential issues with sampling emissions at height such as tanks and flare stacks. Moreover, when we exclude intermittent tank emissions as noted by the baseline OGI survey, the effectiveness in detecting emissions from tanks increases for all teams - Aerometrix (72%), SeekOps (92%) Heath (69%), UofC phase 1 (50%), UofC phase 2 (65%), and Tecvalco (60%). Thus, intermittency of tank emissions should be considered in determining the effectiveness of new technologies that provide snapshot methane measurements.

Table 3: Equipment-level performance showing site-level detection effectiveness (%) for each team in bold across five major equipment types – tanks, wellhead/pumpjack, compressor, separator/dehydrator, and buildings. Overall (%) is the average effectiveness for the team across all equipment types. Data are only for those sites where the equipment was identified by QOGI. Blanks are for those teams which did not report equipment of that kind at all. If QOGI or a team identified a building, while the other identified a compressor or separator/dehydrator it has been marked under both as this equipment in cold regions are often enclosed in buildings, making it difficult for teams to identify the emitting equipment if they are unable to gain access. When adjusted for intermittent tank emissions as identified by OGI - Aerometrix (72%), SeekOps (92%), Heath (69%), UofC phase 1 (50%), UofC phase 2 (65%), Tecvalco (60%).

Technology teams	Overall (%)	Tanks			Wellhead / PumpJack			Compressor			Separator / Dehydrator			Buildings		
		Team		OGI	Team		OGI	Team		OGI	Team		OGI	Team		OGI
		%	#	#	%	#	#	%	#	#	%	#	#	%	#	#
Aerometrix	**70%**	**67**	12	18	**73**	8	11	**40**	2	5	**75**	15	20	**73**	16	22
SeekOps	**81%**	**88**	22	25	**70**	14	20	**67**	4	6	**85**	22	26	**83**	24	29
Heath (Hybrid)	**76%**	**58**	15	26	**63**	15	24	**75**	6	8	**90**	28	31	**88**	30	34
Bridger	**56%**	**25**	1	4							**67**	4	6	**67**	4	6
UofC (phase 1)	**67%**	**32**	9	28	**64**	16	25	**75**	6	8	**82**	27	33	**81**	29	36
UofC (phase 2)	**75%**	**55**	11	20	**43**	6	14	**50**	4	8	**90**	28	31	**91**	30	33
Tecvalco	**34%**	**40**	2	5	**50**	2	4				**30**	3	10	**30**	3	10
FLIR	**30%**				**13**	1	8							**26**	5	19

Third, Bridger Photonics, a plane-based technology, had lower effectiveness in equipment-level detections (56%) compared to other technologies – however, small sample size of 'tier-1' emissions (7 sites) prevent any statistical inference. It was 25% effective in detecting tanks and 67% effective in detecting buildings and separators/dehydrators. The separator and dehydrators detected here are not the ones reported by Bridger, but those where OGI specified that the equipment was in a building, and Bridger successfully identified an emission from a building. Compressors, separators, dehydrators, and other equipment in cold regions are often enclosed in buildings, making it difficult for a plane-based team to identify the emitting equipment.

Finally, both hand-held teams had a lower overall effectiveness at detecting equipment-level emissions compared to other teams. Tecvalco's effectiveness ranged from 30-50% across equipment types for the 10 reported sites. The low number of detections is likely because Tecvalco reported only quantifiable emissions from sources that were safely accessible to attach a flowmeter. FLIR reported emissions only from buildings and wellheads, resulting in a relatively low effectiveness of 26% and 13%, respectively. Furthermore, the uncooled FLIR GF77 infrared camera used by the FLIR team has a significantly lower sensitivity compared to the cooled infrared camera used in the baseline OGI-survey.

4.3 Site-level Emissions Quantification

4.3.1 Flow Rate Quantification

Figure 3 shows the scatter and box plots for site-level emissions quantification at overlap sites for each participating team in AMFC phase 1 and phase 2 campaigns. The sites are shown in descending order of average emissions measured by all teams and the baseline OGI crew. To compare observations across teams, we aggregated all component-level and equipment-level measurements to the site-level. While we analyze quantification performance in comparison to baseline OGI measurements, most jurisdictions with LDAR regulations do not currently require any emissions quantification.

The average site-level emission rate for all sites measured by baseline OGI in phase 1 was 359 ± 146 scfh with median 146 scfh, and in phase 2 was 213 ± 128 scfh with median 91 scfh, respectively. There is wide variation in quantification effectiveness across teams – parity chart of site-level quantification accuracy between teams and baseline OGI for overlap sites show regression coefficients between 0.08 and 0.83 – see SI section 6 for more details.

Site-level emissions quantification varied by over an order of magnitude across all participating teams. The drone-based teams reported average emission rates lower than that of OGI – Aerometrix under-estimated on average by 87% (median 16 scfh, mean 53 ± 37 scfh), and Seekops underestimated flow rates on average by 62% (median 21.3 scfh, mean 134 ± 100 scfh). For the plane teams, Sander estimated an average twice that of OGI (920 scfh) for two overlap sites, and Bridger underestimated by 75% (median 184 scfh, mean 153 ± 113 scfh) for the seven overlap quantified sites. However, these cannot be assumed to be statistically representative because of the small sample size of sites with quantified emission rates.

Both truck teams had better quantification accuracy in phase 2 as compared to phase 1: average underestimation as compared to baseline OGI for Altus was 92% in phase 1 and 76% in phase 2 while that for UofC was 58% in phase 1 and 17% in phase 2. Altus, which measured site-level emissions, estimated an order of magnitude lower emission rate compared to OGI in both phases. In phase 1, Altus estimated a median emission rate of 3.5 scfh (mean 32 ± 33 scfh), compared to baseline OGI median emission rate at overlap sites of 161 scfh (mean 353 ± 162 scfh). In phase 2, Altus estimated a median emission rate of 17 scfh (mean 51 ± 24 scfh), compared to baseline

OGI median emission rate at overlap sites of 88 scfh (mean 137 ± 42 scfh). The UofC average emission rate across all sites were within 25% of OGI in phase 1 (median 292 scfh, mean 402 ± 113 scfh compared to OGI mean 312 ± 146 scfh) but twice that of OGI in phase 2 (median 210 scfh, mean 296 ± 99 scfh compared to OGI mean 144 ± 65 scfh).

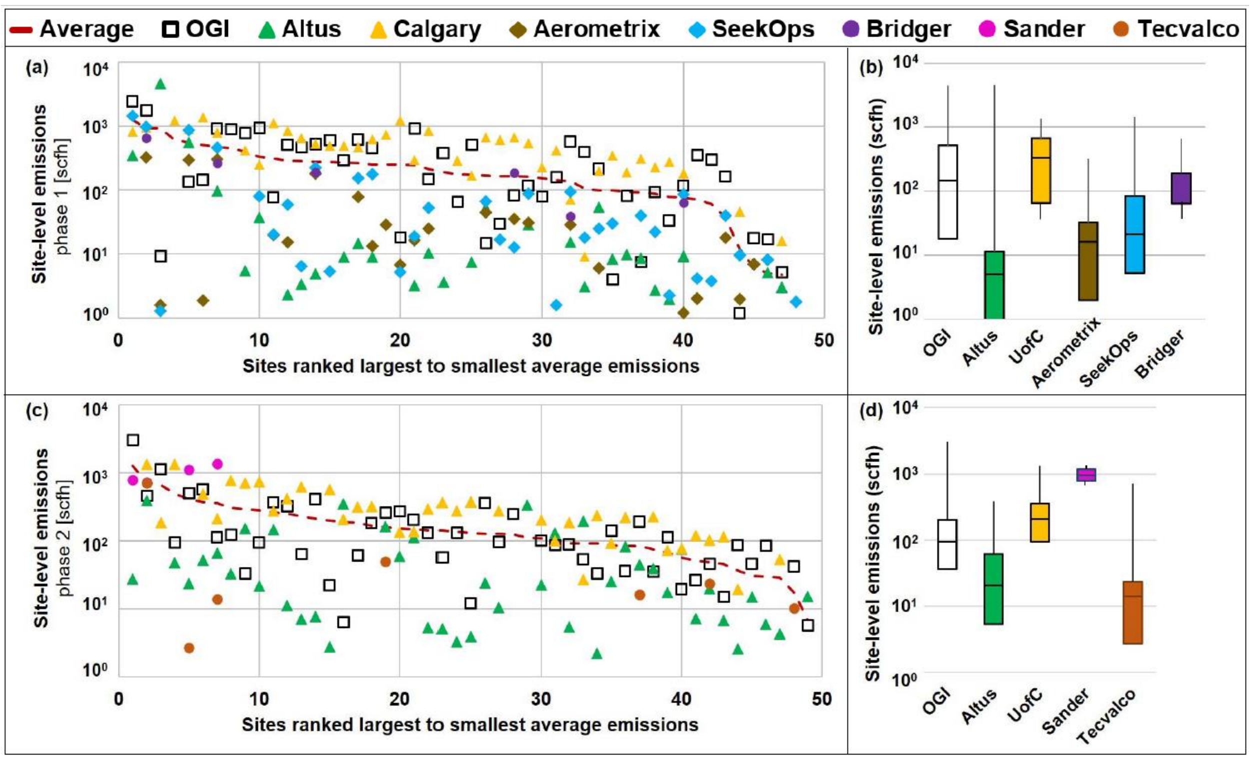

Figure 3: Scatter plot on log scale (y-axis) showing site-level emissions quantification by the participating teams – Altus Geomatics (green triangles), University of Calgary (Yellow triangles), Aerometrix (brown diamonds), SeekOps (blue diamonds), Bridger Photonics (purple circles), Sander Geophysics (pink circles), Tecvalco (brown circles) – and OGI (black squares) at overlap sites in standard cubic feet per hour (scfh) in (a) Phase 1, and (c) Phase 2 of the AMFC program. Sites are ranked from largest average emitting site across all technologies to smallest average emitting site, shown as a red dotted line. (b and d) Box plots show the 25th and 75th quartile range with median site-level emissions, while the error bars (whiskers) show the 10th and 90th percentile.

Tecvalco, the handheld team that quantified component-level emissions, reported a mean emission rate of 92 ± 178 scfh and a median of 14 scfh, that is half that of OGI mean 188 ± 142 scfh. However, Tecvalco's site-level quantification does not include all emissions detected by the team at any given site as quantification was only performed for emitting sources that were accessible and safe. Thus, the underestimation of site-level emissions in comparison to baseline OGI survey is expected.

The underestimation observed between OGI and the teams can arise from several factors. First, not all leaks can be quantified because of accessibility or safety constraints. Second, instantaneous changes to wind directions may prevent an accurate estimation of emission rate, particularly if the technology relies on Gaussian plume dispersion assumptions. Third, potential on-site intra-day variation in emissions may lead to teams measuring vastly different emission rates – this is especially relevant for tank flashing events. Fourth, effectiveness of algorithms that convert raw measurement data to emission flow rates and the design of the sensors may prevent effective measurement of some types of emissions (point source vs. diffused). The critical insight here is that differences in observed emission rates points to the difficulty in effective quantification under field conditions. Efforts to attribute differences in quantification estimates require detailed controlled release experiments that individually test for the impact of confounding variables such as wind direction, wind stability, nature of emission, and emission rate. Furthermore, such field trials of new technologies might require obtaining baseline quantification through multiple, independent methods in the field such as fixed tower sites, tracers, and other established methods to improve redundancy and observe the role of intermittent emissions.

4.3.2 Quantification Rank Parity

Quantification, in general, is a challenging problem [5], [7], [31], [46]. Some technologies propose site-level quantification to triage and direct follow-up close-range inspection for possible repairs. For those reliant on quantification-based triaging, accuracy in ranking the highest and lowest emitting sites is paramount. Figure 4 shows a quantification rank parity chart between teams and OGI, with the highest emitting site as identified by the baseline OGI survey ranked 1. The different shaded regions correspond to sites where the teams ranked within 10%, 20%, and 33% of OGI ranks in either direction. In this analysis, we define accuracy as the number of overlap sites ranked within 20% of OGI ranks.

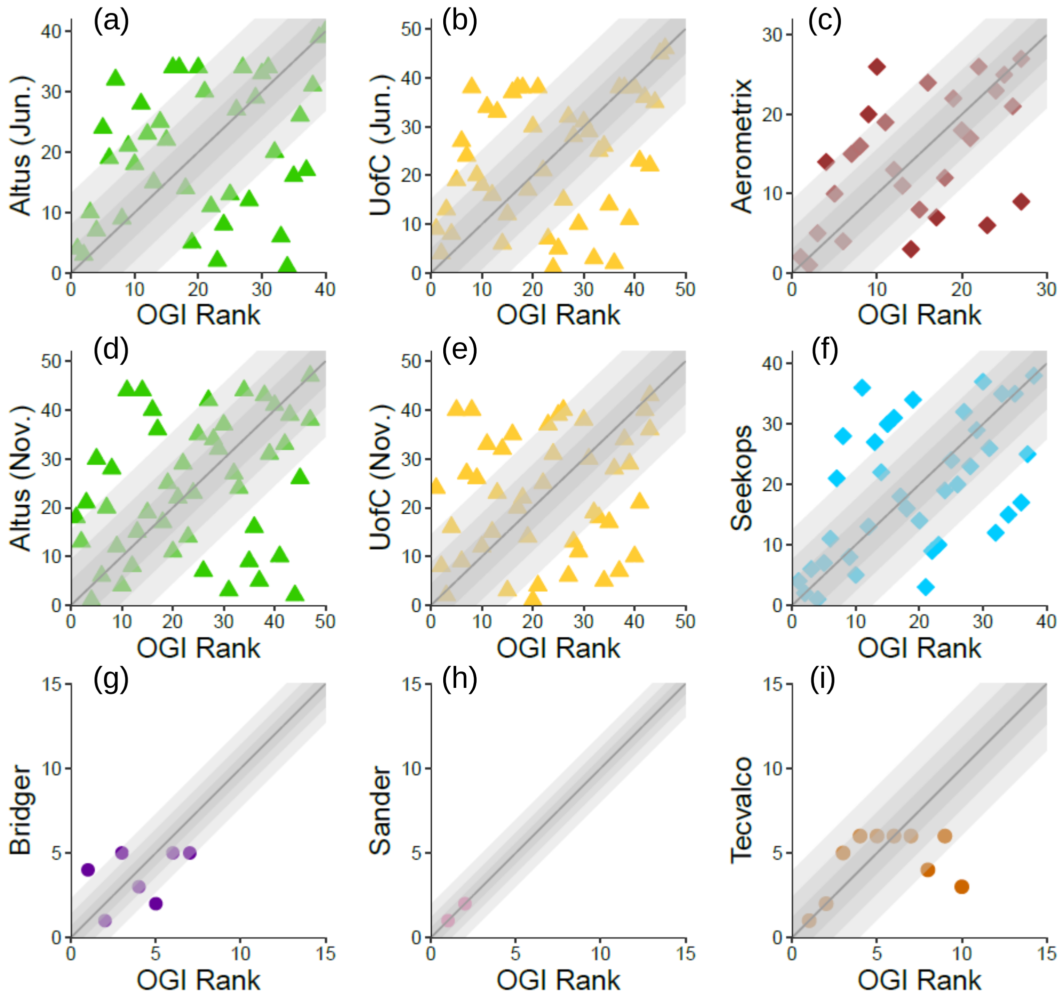

Figure 4: Parity chart of quantification rank between OGI and participating teams. The largest emitting site is given a rank of 1. The two truck teams (UofC and Altus) participated in both June and November campaigns. The black reference line shows a 1:1 relationship where OGI rank = team rank and has a slope=1. The gray shaded region shows where team ranked sites within 10%, 20%, and 33% of OGI ranks (darkest gray = 10%, lightest gray = 33%). Only teams that quantified emissions are shown in this figure.

Drone- and plane-based teams are reasonably effective at estimating the rank-order of site-level methane emissions. Aerometrix and SeekOps demonstrated an accuracy of 57% and 63%, respectively. While the overall correlation between the drone teams and OGI ranking is only moderate (Pearson's correlation coefficient 'r' = 0.5), both teams correctly identified 60% of the top 10 highest and lowest emitting sites in comparison to OGI. Bridger was accurate for three of the seven quantified overlap sites. However, this effectiveness could change as the two plane teams have a relatively small sample size: Bridger with 7 and Sander with 2 sites.

The truck-based teams were between 39-55% accurate across both phase 1 and phase 2 campaigns with a relatively low correlation between their ranks and OGI ranks: Altus with r = 0.3 and r = 0.28 for phase 1 and 2 respectively, and UofC with r = 0.3 and r = 0.17 for phase 1 and 2, respectively. Tecvalco reported quantification data for component-level sources from 10 sites that were accessible and safe to measure. Of these, Tecvalco was within 20% of OGI ranks for 7 sites, where it identically ranked the top two emitting sites similar to OGI.

5. Discussion and Conclusion

The Alberta Methane Field Challenge (AMFC) was the first large-scale, concurrent field trial of alternative methane emissions detection and quantification technologies at operating oil and gas sites. We compared team performance for 12 fixed, hand-held, truck-, drone-, and plane- based technologies to conventional OGI surveys. Most technologies tested were highly effective at detecting site-level methane emissions but demonstrated varying effectiveness in localization, survey speed, and quantification. While this field test is by no means a comprehensive analysis of field performance, the study reveals several insights that would be critical for future scientific research as well as public policy on methane emissions.

First, the hand-held teams showed no significant technological advantage over OGI in detection or quantification performance. While the FLIR team (uncooled IR camera) was faster at site surveys compared to OGI and Tecvalco, it had low detection effectiveness and did not quantify emissions. Alternately, while Tecvalco was highly effective in emissions detection, quantification was limited to safe and accessible sources. In practice, this often excludes high emitting sources such as tanks.

Second, there are distinct advantages of plane- and truck-based teams in survey speed over other technologies tested (drones, and hand-held). However, they will all require some level of secondary close-range inspection to find and repair emitting components. Thus, the effectiveness of technologies that rely on quantification to direct follow-up component-level source identification and repairs risk identifying sites with any methane emission above the detection threshold for potential follow-up. On the other hand, drone-based systems can be effective in detecting emissions that pose access challenges to other ground-based crews. However, they may not provide any significant advantages in terms of survey speed compared to OGI and other hand-held teams.

Most teams are effective at identification of high emitting sites with site-level emissions ranking effectiveness ranged between 43% to 70% of OGI rankings, pointing to their potential use as screening tools. The ability to distinguish between vents and leaks (fugitive emissions) could be beneficial for emissions mitigation programs. Without classification of emissions, sites with ‘allowed’ high venting volumes might be targeted for close range follow-up while sites with leaks but lower overall emissions could be missed. However, except for hand-held teams, no other team consistently identified whether the emissions were from leaks or vents. One way to address this issue would be to cap site-level emissions under regulations – combination of venting and leaks. In that scenario, screening technologies could be deployed for identification of non-compliant facilities for close-range follow-up, but they will need to substantially improve their absolute quantification accuracy.

Many of the technologies tested in the AMFC program show promise for future deployment as part of regulatory LDAR programs. While these results provide critical insight into field challenges encountered by new technologies, it does not provide recommendations on future use (SI section 7). Moreover, this analysis was conducted based on field performance during the AMFC, but actual work practices of these teams might vary as part of LDAR programs. Stakeholders should carefully consider the tradeoffs identified here such as survey speed, quantification accuracy, and spatial resolution before choosing a specific solution. Furthermore, many of the tested systems are in early stages of development and may demonstrate improved performance now. Finally, demonstrating equivalence in emission mitigation between new technologies and conventional OGI-based LDAR programs is still an open challenge and would require a combination of controlled test data, field pilot programs, and modeling [49].

Acknowledgements

Financial support for this research was provided by the Alberta Upstream Petroleum Research Fund and Harrisburg University of Science and Technology. The authors would like to thank Petroleum Technology Alliance Canada and industry participants for providing site access for the study, and critical feedback during the field trial program.

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