Alberta Methane Field Challenge

Final Report

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Executive Summary

The Alberta Methane Field Challenge (AMFC) phase 1 and 2 was a field campaign conducted in 2019 to assess the performance of new methane leak detection and quantification technologies at producing oil and gas facilities.

Background

Recent efforts to address methane emissions from upstream oil and gas operations have led to the development of new sensors, technologies, and platforms that promise faster and more cost-effective methane leak detection than existing approaches. Over the past twelve to eighteen months, several research studies in Canada and the US have evaluated mobile methane detection technologies (drone-, truck-, or plane-based) in controlled test conditions. While these studies are critical to understanding the performance parameters of new technologies, it is insufficient to address questions around their field deployment viability. The AMFC program was commissioned to address this critical gap in evaluation of new methane leak detection technologies.

Program Details

Two separate field trials were conducted in 2019, one in June and the other in November. Each of the field trials consisted of approximately two weeks of testing across 50 oil and gas producing sites near Rocky Mountain House, Alberta. The 50 sites were selected by the AMFC's science team based on several considerations including ease of access, site density to minimize travel time between sites, vegetation type, production, and resource characteristics. A summary of the two field trials including a list of participating teams is shown in Table E1. The leak detection technologies (referred to hereafter as teams) were chosen through a rigorous application and selection process that took into consideration technological capabilities, prior testing experience, deployment and scalability, and cost. In addition, the number of teams using a specific platform (e.g., drone, truck, aircraft etc.) were also limited by the logistics of organizing a safe, large-scale, simultaneous field campaign. In both field trials, Davis Safety Consulting Inc. was selected (through competitive bid) to collect baseline quantified optical gas imaging (QOGI) data to help compare the performance of new technologies with that of the regulatory standard referenced in both Alberta and Canadian federal methane regulations.

Table E1: A summary of the participating teams and technology types tested as part of the Alberta Methane Field Challenge (AMFC) in the June and November 2019 campaigns.

AMFC Phase	Participating Team	Sensor Type	Platform	Detection-level
AMFC phase 1 June 2019	Aerometrix	Tunable open-path laser absorption spectroscopy	Drone	Equipment
	SeekOps Inc.	Miniature methane tunable laser absorption spectroscopy	Drone	Equipment
	University of Calgary	Open-path wavelength modulated spectroscopy	Truck	Equipment
	Altus Geomatics (now GeoVerra)	Cavity ring-down spectroscopy	Truck	Site
	Heath Consultants – 1	Open-path etalon spectroscopy and backscatter tunable diode laser absorption spectroscopy	Hybrid: Truck/ handheld	Component/ Equipment

	Heath Consultants – 2	Long open-path backscatter tunable diode laser absorption spectroscopy	Fixed	Site
	Bridger Photonics	LIDAR	Plane	Site/Equipment
AMFC phase 2 November 2019	Tecvalco	Tunable diode laser absorption spectroscopy	Handheld	Component
	FLIR Technologies	Uncooled infrared camera	Handheld	Component
	Altus Geomatics (now GeoVerra)	Cavity ring-down spectroscopy	Truck	Site
	University of Calgary	Open-path wavelength modulated spectroscopy	Truck	Equipment
	Sander Geophysics	Off-axis integrated cavity output spectroscopy	Plane	Site

Many of the technology tested in the AMFC campaign are early-stage technologies (technology readiness levels 4 – 7) and the results presented here likely represent those from initial field deployment. As such, these results should not be interpreted as being representative of the technologies as they are all likely in continuous and rapid development. This study provides valuable data for operators, regulators, and technology developers to better understand the operational challenges involved in methane emissions detection and quantification using a variety of technologies and platforms. Readers are urged to directly contact the participating technologies to get the most up-to-date performance metrics.

Key Insights

The AMFC yielded several key insights including:

Quantitative optical gas imaging (QOGI) as a baseline technology is effective in providing comprehensive estimates of aggregate methane emissions at oil and gas facilities. Future studies on the precision of QOGI quantification are recommended.

Prior studies of OGI-based, component-level methane emissions at oil and gas facilities used visual estimates and Bacharach Hi-Flow samplers (Hi-Flow) to quantify emissions. While the Hi-Flow provided emission flow rate estimates within 10% error when used correctly and after correcting for gas composition, it had two major challenges – one, it only measured emissions accurately up to 480 standard cubic feet per hour (scfh) (large-emitters at oil and gas facilities can be significantly higher), and two, it can only be used for emissions that are accessible and safe to do so. This prevented some of the largest sources of methane emissions at oil and gas sites – tanks – from being directly measured.

In this study, we used the Providence Photonics' QL320 quantitative optical gas imaging (QOGI) system (in conjunction with a FLIR GF320 OGI camera) to quantify all emissions at oil and gas sites – this is critical to compare site-level emissions estimates to that of other technologies. To validate the instrument (and the thermography team), we conducted approximately 100 controlled release measurements over 11 days as part of the AMFC program. Figure E1 shows the parity chart of the controlled releases and the QOGI estimated rate – we obtain a regression slope of 0.82, demonstrating the efficacy of QOGI to provide reasonable aggregate estimates of emissions.

The aggregate error (18%) from the controlled release tests is comparable to that of the Hi-Flow (~10%). In addition, the QOGI provides estimates for a large range of emissions – from about 10 scfh to over 3000 scfh, significantly higher than the conventional Hi-Flow sampler's limit of 480 scfh. Monte Carlo analysis of these results can help us understand the importance of sample-size in interpreting QOGI data (see full report for detailed analysis). We note that errors in individual emissions measurements can be significantly higher than aggregate estimates. Thus, it is critical for stakeholders to **not** interpret estimates of QOGI-based emissions data individually. We recommend future studies expand on these preliminary results to fully characterize the accuracy and precision of the QOGI instrument in quantifying methane emissions.

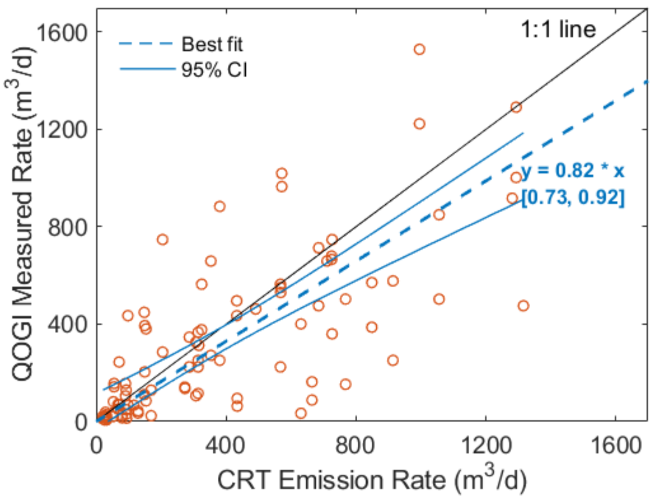


Figure E1: Parity chart of the controlled release test undertaken by the Davis Safety team using the quantitative optical gas imaging (QOGI) method to quantify emissions.

Most technologies evaluated in the AMFC are effective at detecting atmospheric methane concentrations and demonstrate wide performance variation across survey speed, localization, and quantification.

The large number of technologies available for methane leak detection also come with a range of capabilities across tested performance parameters. In the AMFC campaigns, we primarily evaluated technologies across their ability to detect, localize, and quantify emissions. Table E2 summarizes the performance of AMFC participants across four categories – survey rate, measurement time, number of sites visited, and detection effectiveness. A few important observations can be made.

First, all technologies demonstrate high effectiveness in detecting site-level methane emissions compared to the baseline QOGI survey. This is because the detection threshold for most laser-based technologies (including those used by the alternative leak detection platforms) were similar to or better than that of the OGI camera. The FLIR Systems Inc. (FLIR) uncooled infrared camera (FLIR GF77) evaluated in the AMFC had a significantly lower detection effectiveness compared to cooled infrared camera (FLIR GF320) used in the baseline QOGI survey – this is because uncooled infrared cameras have significantly lower sensitivity than cooled infrared cameras.

Second, survey rates varied from 3 sites per day for Tecvalco (AMFC phase 2) to 15 sites per day for Altus Geomatics (AMFC phase 1), indicative of the type of survey performed by the two technologies. Tecvalco is a hand-held system that identifies component-level emissions and quantifies emissions using a flow meter – while this produces high quantification accuracy, survey speeds are lower than that of baseline OGI. Altus Geomatics provides site-level emissions estimates that are intended to be used to quickly tag high-emitting sites for future follow-up – while the high survey speed is attractive, the ability to identify high-emitting sites is dependent on quantification accuracy. The survey rate shown here can be interpreted to be a conservative lower bound on realistic survey speeds when implemented as part of an LDAR program. This is because teams in the AMFC challenge sometimes had to wait for other teams on a site to finish measurement, resulting in delays. Furthermore, coordinating with all participating teams on site-visits will result in a site-visit routing that might be sub-optimal compared to a scenario where only one technology was measuring emissions.

Third, the measurement time on site also varied between teams – from under 10 minutes per site for Altus Geomatics, University of Calgary, and Bridger Photonics, to over 30 minutes per site for other teams (see Table E2). This results from a combination of factors such as measurement detail (component vs. site level) and deployment method (truck vs. on foot vs. plane). It is expected that any of the teams participating in the study could survey sites faster without the experimental restrictions of the program or unique weather challenges at the study site (e.g., afternoon thunderstorms). Drone-based platforms, for example, also require time to set up and take down their technologies during which time they are not actively measuring. Similarly, the University of Calgary system also spent more time than shown here on a site while collecting ancillary scientific data that would not be collected as part of an LDAR program.

Overall, aerial and truck-based systems have distinct advantages in survey speed over other ground-based technologies. However, they will all require secondary inspection to find and potentially repair the emitting component. Thus, the ability of *'fast technologies'* to perform as effective screening systems to identify high-emitting sites rests on their quantification effectiveness. Without reasonably effective quantification, these systems risk identifying sites with any methane emission above the detection threshold for potential follow-up. Drone based systems can be effective in detecting and quantifying methane emissions in situations that pose access challenges. The combination of three degrees of freedom and ability to measure close to the emission source makes drones effective at quantifying sources such as flares or tanks more easily than conventional Hi-Flow based approaches. However, there are not significant advantages on survey speed compared to OGI-based LDAR surveys.

Table E2: Summary of the performance of all participating technologies in both trials of the AMFC challenge including survey speed, measurement time, total sites visited, and detection effectiveness. Here, detection effectiveness is defined as the fraction of sites with methane emissions by the technology to that of OGI.

Team	Method	Total participa-tion days	Survey Rate (sites per day)	Measurement Time (min per site)	Number of Sites Visited	Detection Effectiveness (site-level, %)
	AMFC phase 1					
Univ. of Calgary	Truck	12	8	10	90	81%
Altus Geomatics (GeoVerra)	Truck	10	14	9	127	87%
SeekOps	Drone	11	5	36	54	92%
Aerometrix	Drone	10	5	20	44	80%
Heath (hybrid)	Truck + handheld	12	5	41	53	91%
Bridger Photonics	Plane	5	13[1]	7	65	35%[2]
	AMFC phase 2					
Univ. of Calgary	Truck	11	5	6	54	90%
Altus Geomatics (GeoVerra)	Truck	11	8	5	90	94%
Tecvalco	Handheld	5	3	52	14 (10)[3]	89%
FLIR	Handheld	5	5	36	26	29%

Sander Geophysics	Plane	7	6[4]	23	39	100%[5]

[1]Based on daily flight time of 2 – 3 hours per day
[2]Only refers to 'tier 1' emissions. This increases to 90% if 'tier 3' emissions are included. See full report for details.
[3]Although 14 sites were visited by the Tecvalco team, data for only 10 sites were provided.
[4]Based on a flight time of 4 – 5 hours per day.
[5]Only refers to emissions detection. However, Sander Geophysics only quantified emissions at 4 of the 32 overlapping sites because of unstable wind conditions. See full report for details.

Accurate quantification remains challenging – some technologies can provide good order of magnitude estimates of site-level emissions compared to QOGI.

Significant variation in quantification ability across technologies result from a combination of algorithmic efficacy, survey method, spatial and temporal characteristics of site emissions, atmospheric conditions, and measurement uncertainty. These results have also been observed in prior controlled studies and have been attributed to algorithmic challenges in translating raw methane concentration data into flow rate information. Figure E2 and Figure E3 show the site-level emissions of participants in the AMFC phase 1 and 2 field campaigns, respectively. Importantly, not all AMFC participating teams offered or provided methane emissions quantification. The following discussion pertains only to those teams evaluated for emissions quantification. We make several important observations.

First, site-level emissions quantification shows significant variation across teams. While the QOGI and University of Calgary team reported similar average emissions in both AMFC phase 1 and 2, other teams generally underestimated emissions relative to QOGI. Only the Sander Geophysics team reported emissions significantly higher than that of QOGI in the AMFC phase 2 campaign – however, Sander was only able to quantify emissions at 4 sites because of unstable wind conditions and thus are not statistically representative.

Second, drone-based and aerial teams were effective at correctly estimating the rank order of site-level methane emissions. For example, sites that showed the highest emissions in the QOGI survey in AMFC phase 1, also exhibited high emissions among other technologies, even if the absolute emissions estimates were different. This implies that some technologies could be effective at classifying whether sites have low, medium, or high emissions and could point to their use as effective screening tools. Improvements to quantification will directly improve classification ability.

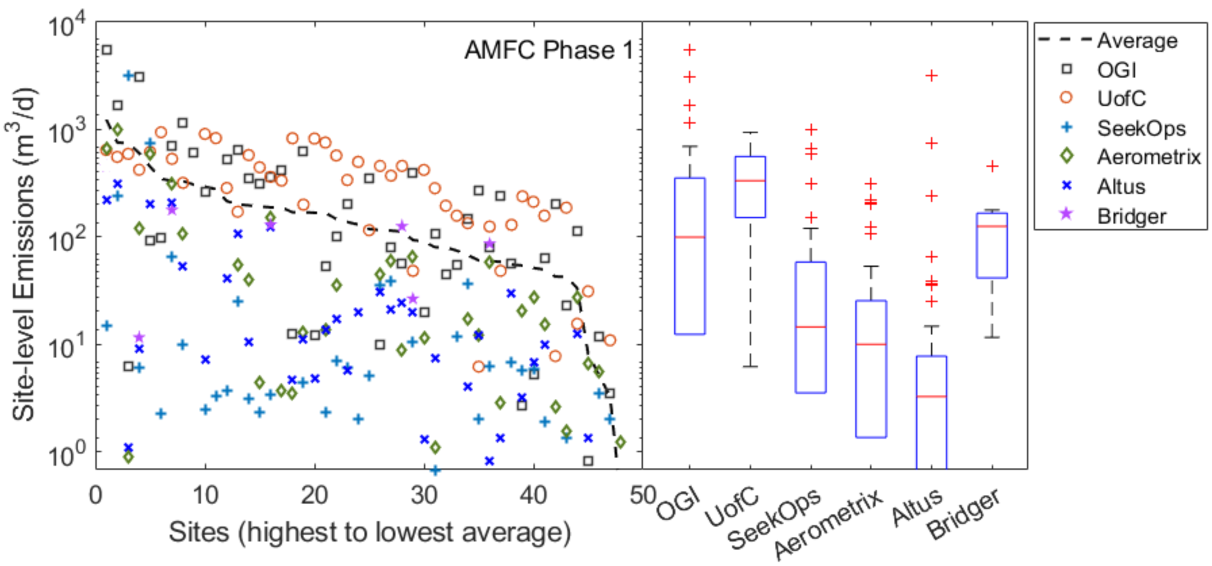


Figure E2: Summary of AMFC phase 1: Aggregated site-level emissions by all participating teams in the AMFC phase 1 program that quantified emissions. (a) Sites are arranged from highest to lowest average emissions detected by all teams (black dashed line), with individual scatter plots representing participating technologies – OGI (grey squares), University of Calgary (orange circles), SeekOps (blue plus sign), Aerometrix (green diamonds), Altus Geomatics (blue cross sign), and Bridger Photonics (pink stars). (b) Box plots of emissions detected by the six technologies represented in (a).

Third, site-level quantification shown in these figures do not necessarily represent the total site-level emissions that a technology could have measured. The site-level data shown here were aggregated from equipment-level data at each site for technologies that reported at the equipment level. In many cases, we found that these technologies were not able to detect (or quantify) all emissions that were detected by the QOGI team at that site. Therefore, these site-level estimates likely represent the lower-bound for technologies that undertake equipment-level surveys.

Fourth, the underestimation between QOGI and other technologies in developing site-level estimates can also result from other potential issues: instantaneous wind conditions that prevented an accurate estimate, potential on-site changes in intermittent emissions, effectiveness of algorithms that convert raw data to flow rate information, design of the sensor platform that prevents effective measurement of some types of emissions, or the nature of emissions (point vs. diffused). Equipment leaks from those that are enclosed in buildings and leak or vent through broken seals present a diffuse emission source that might be difficult to detect and quantify as typical plume inversion models would not be effective in characterizing it.

Fifth, the average site-level emissions in AMFC phase 2 is approximately 50% of those detected in AMFC phase 1 by the baseline QOGI survey and two teams that participated in both trials –University of Calgary, and Altus Geomatics. This indicates both that winter-time emissions may be lower than summer-time emissions (e.g., lower temperatures lead to less out-gassing from liquids) and that the three technologies are relatively consistent in the emissions estimates across seasons. In-situ controlled release tests can be further used to calibrate the quantification ability of all technologies.

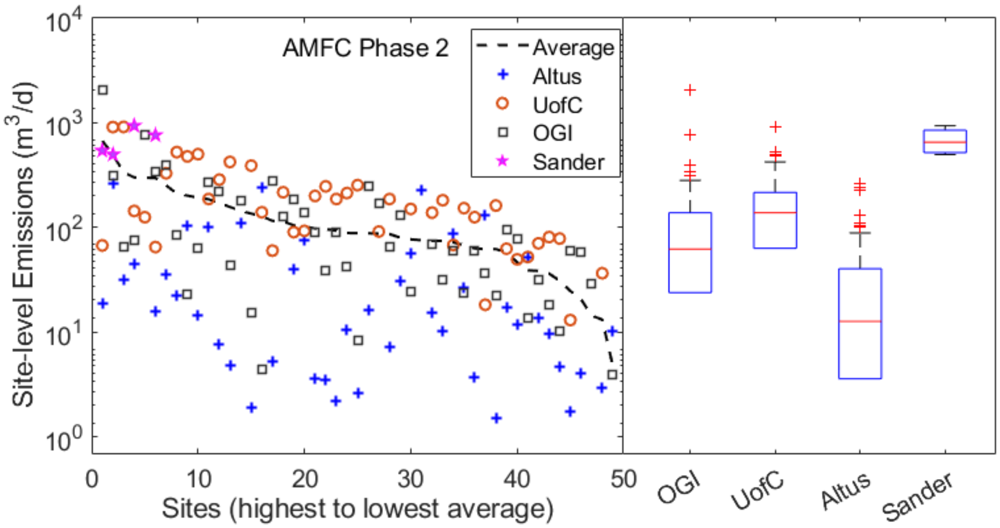


Figure E3: Summary of AMFC phase 2: Aggregated site-level emissions by all participating teams in the AMFC phase 2 program that quantified emissions. (a) Sites are arranged from highest to lowest average emissions detected by all teams (black dashed line), with individual scatter plots representing participating technologies – OGI (grey squares), Altus Geomatics (blue plus sign), University of Calgary (orange circles), and Sander Geophysics (pink stars). (b) Study-average emissions detected by the four technologies represented in (a).

The fixed sensor tested in this study was effective at detecting methane emissions. However, given the amount of data collected, significant effort is required to convert it into site-specific actionable information.

The AMFC campaign tested one laser-based fixed sensor with a backscatter target (Heath Consultants) that was installed for approximately six months from June to November 2019. The sensor collected data on methane concentration-pathlength, wind speed, and wind-direction continuously every 2 minutes, and data were uploaded to the cloud in real-time. Based on the testing and analysis of this technology, we can provide some preliminary insights into fixed sensors.

Fixed sensors generate significant amounts of data in a short time, providing site-level methane emissions information at a high frequency. Such data, when combined with site-level knowledge, could become a powerful tool in addressing methane emissions. Furthermore, the continuous data provided by fixed sensors can be used to improve our understanding of temporal changes in methane emissions at oil and gas sites and help reduce emissions significantly faster than what a periodic LDAR survey would allow.

However, fixed sensors also require significant analytical capabilities to support the raw data collected by the sensor. In the AMFC challenge, the sensor only provided read outs of methane concentration path-length, wind-speed, and wind-direction as a function of time. Processing these data to evaluate the location of the emission, its nature (vent vs. leak, continuous vs. intermittent), and size is critical for its use in any LDAR program. We undertook this analysis partially and show that fixed sensor data can be used to identify potential emission location, nature of emission, and time of emission using prior knowledge of the site layout. It is essential for fixed sensor technologies to develop the analytical platform for it to be applicable in leak detection and repair programs. The technology tested in this study is only a methane sensor, not yet a methane detection solution.

In-field controlled releases are effective in assessing the quantification capabilities of new technologies that account for local weather conditions.

The performance of technologies is affected by weather conditions to varying degrees. OGI cameras have reduced sensitivities in high wind conditions or cloudy days. Truck-based systems may have difficulty in detecting emissions at height (tanks or flares) depending on wind and atmospheric boundary layer conditions. Similarly, drones may find it challenging to map flow rates from concentration profiles on low-wind days without significant plume dispersion. While controlled release tests (CRT) conducted separately to characterize a technology are useful, it is not possible to test new technologies under all possible conditions that can be experienced in the field. Therefore, it is possible that field performance does not reflect tests conducted under ideal conditions.

To solve this challenge, the AMFC phase 2 field campaign employed in-field controlled releases to assess the quantification ability of various technologies. A CRT set-up was installed on an undeveloped, non-operating oil and gas site that was carefully checked for any non-test methane emissions from nearby oil and gas operations. Two release points, one at 5 ft and the other at 15 ft, were set up and known natural gas flow rates were released through a pressure-dependent flow meter for each team to quantify. Each team was required to visit the controlled release test daily and test between 3 and 5 releases. These in-field tests are cost-effective, convenient, and greatly improve the confidence in emissions data provided by new technologies. Furthermore, because these tests occur contemporaneously as the actual oil and gas site survey, the impact of wind, weather, and other atmospheric conditions are factored into the controlled releases. Therefore, these CRT tests provide an ideal platform to assess technology quantification performance in real-time. Future work with new technologies, whether as part of a research study or an LDAR survey, should strongly consider employing such in-field controlled releases to improve the quality of the data collected.

1. Introduction

The Intergovernmental Panel on Climate Change (IPCC), in its recent special report on global warming of 1.5°C, highlighted the importance of reducing short-lived greenhouse gases (GHG) like methane [1]. Methane is a major component of natural gas and has a warming potential that is significantly higher than that of carbon dioxide. Addressing methane emissions from the oil and gas industry is critical to maintain the sustainability of natural gas even as Canada makes progress towards net-zero emissions [2]. Furthermore, reducing methane emissions also reduces emissions of volatile organic compounds thereby improving local air quality [3], [4].

Canada has recently developed regulations to reduce fugitive (unintentional) and vented (intentional) methane emissions from upstream oil and gas facilities [5], [6]. A major component in reducing fugitive methane emissions is periodic leak detection and repair (LDAR) surveys at different survey frequencies based on the type of facility. These LDAR surveys, extensively used in Canada and the US, typically require the use of specific methodologies such as U.S. Environmental Protection Agency (EPA) Method-21 or optical gas imaging (OGI) systems [7]. OGI systems have been more universally adopted over the years because of their ease of use and ability to visualize methane emissions. Furthermore, recent evidence suggests that they can be effective in reducing emissions [8]. Although OGI-based LDAR surveys have been widely adopted, there are two challenges. One, a ground team consisting of one to two crew members can cover about 5 – 6 simple sites per day (e.g., single well sites). Regulations that require LDAR surveys of thousands of wells multiple times a year could quickly become time consuming, expensive and increase health and safety risks owing to the significant "windshield" time associated with multiple site visits. This is especially challenging when low gas prices prevent operators from realizing the economic benefits of conserved gas. Two, the use of OGI-based surveys comes with its own limitations, such as the need for favorable atmospheric conditions and operator experience [9], [10]. Thus, there is a need for leak detection technologies and methods that are faster and more cost-effective than existing approaches. Even if new technologies cannot fully replace existing OGI systems, they could provide complementary services that could potentially reduce the costs associated with such periodic surveys [11]. However, costs were not explicitly evaluated during the AMFC program.

Recently, there have been many studies in Canada and the US that make use of mobile and aerial systems for methane emissions detection [12]–[21]. Incidentally, these studies have often revealed discrepancies between observed and reported emissions [12], [22], [23] – these result from a combination of outdated emission factors, errors in activity factors, definitions around reportable and non-reportable emissions, and temporal variability of methane emissions. This anecdotal evidence points to the potential effectiveness of some of these new systems to be better able to detect and measure methane emissions than component-level ground surveys. Some research groups have also experimented with unmanned aerial vehicles to detect and quantify methane emissions at upstream and midstream oil and gas facilities [24], [25]. At the other end of the technology spectrum, satellite technologies have been used to study regional and global methane emissions from anthropogenic and biogenic sources [26], [27] – many start-up companies and non-governmental organizations in Canada and the US are now in the process of deploying satellites that can detect methane point sources associated with oil and gas activity [27]. A systematic review of the promise of new methane leak detection technologies and potential scientific and deployment challenges can be found in Fox et al. [11].

Until recently, there has been no systematic study of alternative approaches to methane emissions detection and quantification. The Stanford/EDF Mobile Monitoring Challenge conducted in 2018 tested ten truck-, drone-, and plane-based systems for their effectiveness in detecting and quantifying methane emissions at a controlled release testing facility [28]. Stakeholder workshops conducted in Canada and the US have underscored the importance of testing new technologies before they can be deemed equivalent to existing emissions reductions approaches [29]. These workshops resulted in the development of a framework for technology equivalence that recommended new methods to go through rigorous controlled release testing, modeling, and field trials to understand equivalence to conventional OGI-based approaches [29], [30]. While there has been some existing work on controlled release testing and modeling, there have not been any large-scale field trials of new methane detection technologies.

In this work, we report results from the first large-scale field trial of alternative methane emissions detection and quantification technologies at producing oil and gas sites in Alberta, Canada. This project – called the Alberta Methane Field Challenge or AMFC – tested five different types of leak detection methods: fixed continuous monitoring systems, handheld devices, truck-mounted sensors, drone-mounted sensors, and aerial systems. The field trials were conducted at 50 oil and gas sites and split into two phases –AMFC phase 1 occurred in June 2019 with 7 technologies, and AMFC phase 2 occurred in November 2019 with 5 technologies. In addition to the participating teams, the AMFC also included a baseline quantified OGI (QOGI) methane emissions survey at each site to make relevant performance comparisons to currently approved regulatory approaches.

This report is divided into 8 sections. Section 1 is this introduction followed by a detailed account of study design and methodology in Section 2. Section 3 provides a detailed discussion of emissions estimates using a QOGI system in order to provide the reader with an understanding of uncertainties associated with the baseline QOGI survey and the subsequent interpretation of emissions estimates from new technologies. Section 4 explains the metrics used to evaluate the performance of participating teams. Sections 5 and 6 describe results from the AMFC phase 1 and 2 campaigns, respectively. Section 7 discussions study limitations and section 8 provides a brief conclusion followed by a bibliography.

2. Study Design and Methodology

The Alberta Methane Field Challenge (AMFC) took place in two phases – phase 1 was executed in June 2019 and phase 2 was executed in November 2019. While the two phases were planned and organized independently, many of the design elements were kept consistent across both phases to better enable comparison of technology performance. Participating teams measured methane emissions at 50 oil and gas sites, and measurements were compared to those of conventional (quantified) optical gas imaging (QOGI) surveys. A summary of the participating teams in each of the two phases is provided in Table 1.

Table 1: List of teams that participated in the two phases of the Alberta Methane Field Challenge

AMFC Phase	**Participating Team**	**Sensor Type**	**Platform**	**Detection-level**
AMFC phase 1 June 2019	Aerometrix	Tunable open-path laser absorption spectroscopy	Drone	Equipment
	SeekOps Inc.	Miniature methane tunable laser absorption spectroscopy	Drone	Equipment
	University of Calgary	Open-path wavelength modulated spectroscopy	Truck	Equipment
	Altus Geomatics (now GeoVerra)	Cavity ring-down spectroscopy	Truck	Site

	Heath Consultants – 1	Open-path etalon spectroscopy and backscatter tunable diode laser absorption spectroscopy	Hybrid: Truck/ handheld	Component/ Equipment
	Heath Consultants – 2	Long open-path backscatter tunable diode laser absorption spectroscopy	Fixed	Site
	Bridger Photonics	LIDAR	Plane	Site/Equipment
AMFC phase 2 November 2019	Tecvalco	Tunable diode laser absorption spectroscopy	Handheld	Component
	FLIR Technologies	Uncooled infrared camera	Handheld	Component
	Altus Geomatics (now GeoVerra)	Cavity ring-down spectroscopy	Truck	Site
	University of Calgary	Open-path wavelength modulated spectroscopy	Truck	Equipment
	Sander Geophysics	Off-axis integrated cavity output spectroscopy	Plane	Site

2.1. Technology Team Selection

The AMFC consisted of the participating technologies ('participants'), the science team, the project management team, and the steering committee. The science team included Arvind Ravikumar and Devyani Singh at Harrisburg University and Chris Hugenholtz at the University of Calgary. The project management team included Brenna Barlow and Wes Funk of DXD Consulting Inc. and Andrea Cosgrove and Cooper Robinson of Radicle. The science team and the project management team together are referred to as the 'study team' in this report. The steering committee included representatives of various operators, Petroleum Technology Alliance of Canada (PTAC), Canadian Association of Petroleum Producers (CAPP), and provincial and federal regulatory agencies.

The AMFC participants were selected through a rigorous application process that included four steps.

a. **Step 1:** An open invitation was placed on PTAC's website. All interested parties were required to complete and submit a detailed application that requested information on their organization, technology and method specifications, and business plan and costs of their system. The application for both AMFC campaigns were nearly identical with minor modifications to reduce ambiguity based on feedback from the steering committee. The full application is shown in Appendix A. The recruitment of the QOGI team was undertaken using a competitive bid process that evaluated technical offerings, resourcing, and commerciality.
b. **Step 2:** All teams were first evaluated by the science team against established criteria such as technological capabilities (detection limits, survey speed, etc.), prior field or test experience, logistical challenges, and whether detailed controlled release test-data were available for evaluation by the science team. This evaluation was then used by the steering committee in making decisions about the team selection.
c. **Step 3:** The steering committee (committee) for the project were provided with the detailed evaluation of each team conducted by the science team. The committee then used this feedback to evaluate each application on a score of one to five along four categories: performance and specifications, technology readiness and scalability, business factors, and team composition. The scores from all committee members were averaged to obtain a ranked list of applications for participation. Typically, higher scoring teams were selected to participate in the field campaign. However, other logistical considerations were also included in the selection process. For example,

it would have been logistically difficult to simultaneously operate more than 1 plane or 2 drones as part of the field program. Therefore, only the top two drone teams were selected for the study.

d. **Step 4:** Finally, the teams were informed of their selection and asked to confirm participation by signing contracts. After the teams confirmed their participation, the study team began detailed conversations with each participating team to inform planning, ensure compliance with all safety certifications (including operator-specific certifications) and field execution.

2.2. Study Region and Site Selection

Study Region: Sites near Rocky Mountain House were selected for both AMFC campaigns for multiple reasons. One, the region was already familiar to the study team and the QOGI team (i.e., Davis Safety) who had been involved in other projects in the area. Two, the operators in the steering committee had assets in the region and were willing to grant site access to measure emissions at these sites as part of the project. Three, it was one of the most easily accessible areas from Calgary, which is important given the participation of several international teams. Four, the oil and gas sites in the Rocky Mountain House area have higher spatial density relative to other production regions of the province, which reduces driving time between sites, and increases the amount of data that can be collected. Five, within the study region, sites were available to the study that had a wide range of characteristics, detailed in the Site Selection section below. Finally, Rocky Mountain House has served as a base for the oil and gas industry and oilfield services for decades, making it a logistically prime municipality to serve as the base for a large and complex field program.

Site Selection: The science team conducted detailed analysis of the sites in the region and considered several factors while selecting sites for the AMFC program. These factors included vegetation type (forested vs. prairie), production, site-size, ease of access, site density, representativeness of the selected sites to assets in the larger Red Deer producing region, operational status, site applicability to provincial and federal regulations, and representativeness of the equipment typically used in this region. Figure 1 shows the Google Earth image of the 50 sites selected for the AMFC program.

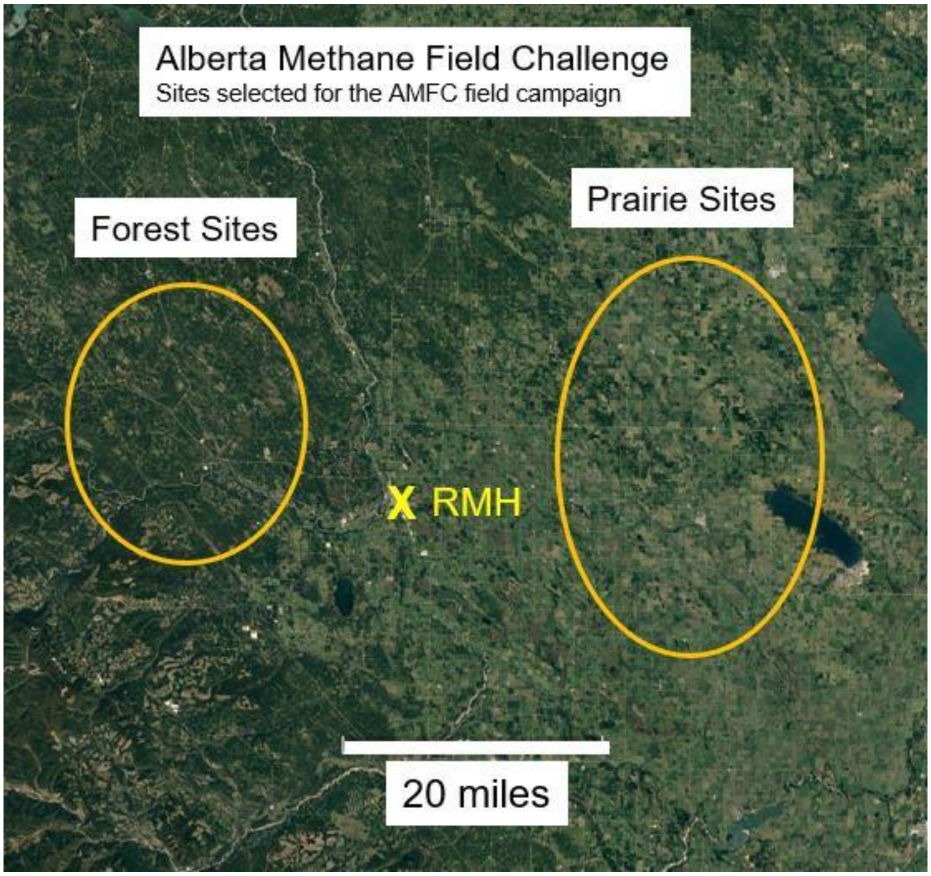


Figure 1: Google Earth image of the Red Deer region used in the AMFC challenge, indicated a mix of forested and open-prairie sites. Rocky Mountain House (RMH) is indicated by a yellow X.

2.3. Controlled Release Test (Phase 2)

Phase 2, conducted in November 2019, also included a controlled release test (CRT) site where known methane release rates were used to calibrate the quantification accuracy of each technology. The CRT set up was not intended to exhaustively evaluate the performance parameters of a technology such as detection probability curves as conducted in prior studies [28]. The goal of the CRT was to evaluate the quantification accuracy across a wide range of emissions rates typically observed at oil and gas sites. Therefore, the CRT tests provide a quantification calibration for observed oil and gas methane emissions where the ground truth is unknown. The CRT set-up, organized by Nitrogen Technologies of Canada (NTOC) consisted of two release points at 5 ft and 15 ft on an open, undeveloped, non-operating oil and gas site that was located near the field study sites. Assessing quantification accuracy at two different release heights helps evaluate the quantification accuracy of technologies under differing air flows around release points, atmospheric dispersion, imaging background, and simulates the presence of equipment at different heights at oil and gas facilities. The CRT site was carefully surveyed prior to the program to ensure there were no interfering methane emissions from the site, and there was no operating equipment at the site. NTOC sourced gas from ATCO with a methane content of 89.86 %. Gas was transported and stored in cylinders within a trailer and was regulated down to appropriate pressure prior to the release points. A heat exchanger was also used to regulate the temperature of the gas to near-ambient conditions. NTOC staff monitored flow rates continuously during all releases, and release rates were logged electronically at a 15-second interval.

The release rates in the CRT experiments were chosen to mimic both equipment-level and site-level emissions typically observed in other field studies. In practice, the CRT releases spanned about three orders of magnitude: from a low of about 20 standard cubic feet per hour (scfh) (~13.6 m^3/d) to a maximum of about 2000 scfh (~1340 m^3/d). The distribution of controlled release rates was such that only 20% of all releases were greater than 1000 scfh. Figure 2 shows the histogram of the CRT release rates used in AMFC phase 2. Every team was required to visit the CRT site daily to participate in 3 – 5 controlled releases per day. Teams were generally not allowed to use any on-site equipment as a background for measuring the controlled releases. However, multiple teams could measure a release simultaneously provided one team's measurement did not interfere with the other team (e.g., a plane-based and truck-based technology measuring simultaneously).

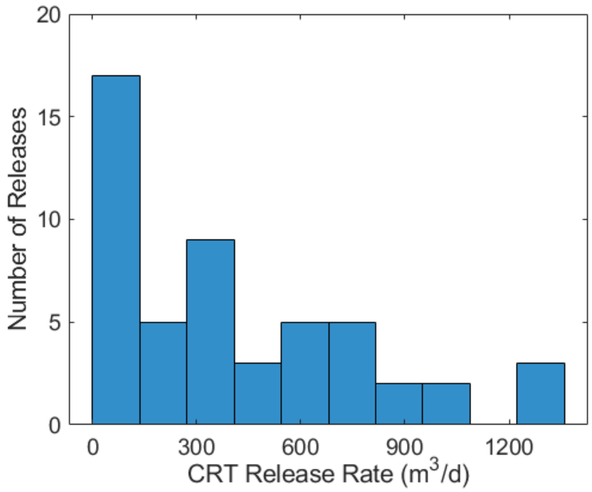


Figure 2: Histogram of the controlled releases used to calibrate the quantification accuracy of team participating in AMFC phase 2 in November 2019. 80% of emission rates were less than 1000 scfh.

2.4. Field Campaign

2.4.1. **Orientation:** Both phases of the AMFC field campaigns were preceded by a day long orientation, and attendance was mandatory for all individuals that were participating in the field. Prior to this orientation day, all teams were provided with an orientation package that included detailed descriptions of the activities to be completed before they were permitted to measure emissions at oil and gas facilities. Because the measurements were undertaken at producing oil and gas sites, and some of the teams were relatively new to operating at upstream production facilities, it was critical to brief all participants on site permitting, health and safety, and emergency protocols during the entire program. All teams underwent a spot check on appropriate safety gear, certifications, and signed site-access agreements with the three operators. Figure 3 shows a group picture of all the participating and study team members that were part of AMFC phase 1, taken at the end of the orientation day.

Figure 3: Group picture of the participating and study teams after orientation day before the June 2019 AMFC challenge.

2.4.2. **Field Scheduling:** Site scheduling was critical to the success of the AMFC program – coordinating measurements across multiple teams such that they overlapped with the baseline QOGI survey was necessary to compare emissions data from the teams. The OGI crews were provided with a fixed schedule of sites to survey each day. In general, this schedule was slightly slower than typical survey speeds for QOGI-based leak detection surveys to accommodate any unanticipated delays when working with multiple simultaneous measurements. The sites that were visited by the QOGI crew were mandatory for all teams to visit on the same day – the teams were allowed to visit the 'mandatory sites' at any point during the day as long as two teams do not measure in a manner that is inconsistent with independent measurements. In addition to these 'mandatory sites', participating teams could visit 'additional available sites' if they finished the mandatory sites for the day.

2.4.3. **Field Protocol:** The participating teams were required to follow the site schedule. Each day started with a morning briefing led by the study team going over the details of that day's site schedule using satellite images and planning the order in which teams were to arrive on site. An informal site-visit order was developed at the morning briefing, so all teams started in non-overlapping positions. Depending on the survey speed, it was possible for two teams to end up on the same site simultaneously through the course of the day. In these scenarios, the team that first arrived at the site would complete their measurements while the second team waited. Because the number of sites that a team covered on any given day depended on unintended delays (e.g., waiting for a team to finish measurements) that is unlikely to happen in real-world scenarios, the survey speed data in this report should be interpreted with caution.

2.4.4. **In-Field Communications:** The study team established a secure mobile text-based communication channel (Slack) for exclusive in-field communications through the study. All participants had access to the channel and could send messages to everyone or to the study team individually. The teams used this to announce the site they were heading to or leaving, letting others know that the site is currently being measured or available for measurement, respectively.

2.4.5. **Data Handling and Reporting:** The study team created detailed data sharing and data recording policies for three critical reasons – one, security of non-anonymized data, two, meaningful comparisons with the OGI baseline data, and three, ease of reproducibility for future field campaigns. The data reporting policy outlined how each participating team was required to deliver data to the study team, and what data were required.

The data sharing policy details how information/data given to and collected by participating teams must be handled, given that the data may be confidential. Each team was required to submit emissions data in an excel file in a specified format that included information on weather, survey times, emissions detection and localization, quantification (in flow rates, not concentration), list of equipment and components surveyed, and any comments that would help the science team interpret the data. In addition, the teams were also required to submit supporting evidence to validate the reporting in the excel file – in this case, the teams were allowed to submit 'evidence' in any format they wished including KMZ files, PPT, images, etc. The data reporting and data sharing policy that were developed for the AMFC program are provided as Appendices C and D to this report.

3. Interpreting QOGI Data

The quantitative optical gas imaging (QOGI) tool (QL-320) developed by Providence Photonics is an external accessory to the FLIR's GF-320 OGI camera to quantify emissions [31]. In AMFC, the Davis team used the GF-320 to detect emissions and QL-320 to estimate emission rate, collected referred to as the 'QOGI measurement' throughout this report. The QL-320 operates by identifying the methane gas plume pixels on the camera and calculating the effective absorption cross-section (concentration path-length) of the emissions source at each pixel [10]. To calculate this, the thermographer must input measurement details such as temperature, nature of plume (absorptive or emissive), imaging distance, and wind speed.

The detection limit of the OGI camera and consequently the QOGI quantification algorithm depends on a number of external factors such as background irradiance, apparent temperature contrast, wind speed and turbulence, and imaging distance [32]. However, the calibration procedure employed by Davis Safety to adjust the imaging distance daily based on their observations of a standard hydrocarbon gas source helps to compensate for weather-dependent changes to detection accuracy.

Although the QOGI was tested with controlled releases during the second phase of the AMFC study, we discuss the results of this testing first to help interpret the results from other participating teams evaluated in the AMFC program. Understanding how to interpret quantification results from the QOGI is critical for three reasons: one, it helps provide appropriate context to evaluate new technologies and avoid the fallacy of assuming that the QOGI measurement is the ground truth; two, it helps differentiate between errors in individual measurements versus aggregate data that is important for understanding average emissions; and three, it provides businesses and regulatory agencies with the statistical background necessary to interpret QOGI data from any other field study.

In the AMFC, there were two QOGI field crews to detect and measure emissions at producing oil and gas sites. With the introduction of controlled release testing in phase 2, both QOGI teams collected independent measurements at the controlled release site as a part of their daily schedule of site visits. The OGI crews were tested on the same controlled release emission rates as for all participating teams – these emission rates were roughly equally split across the two emission heights: 5 ft and 15 ft. Across 11 days of the AMFC phase 2, each of the two OGI field crews took part in approximately 50 controlled releases, thus providing around 100 individual data points for evaluating the accuracy of QOGI emissions estimates.

Figure 4 shows a parity chart of the controlled release emission rate and the QOGI emission rate for both field crews, which measured independently of each other. A least-squares linear regression across all data points gives a slope of 0.82 with an R^2 value of about 0.6. The slope has a 95% confidence interval between 0.73 and 0.92 – this should be interpreted not as an underestimation by the QOGI but that the likelihood of the true slope being between 0.76 and 0.92 is 95%.

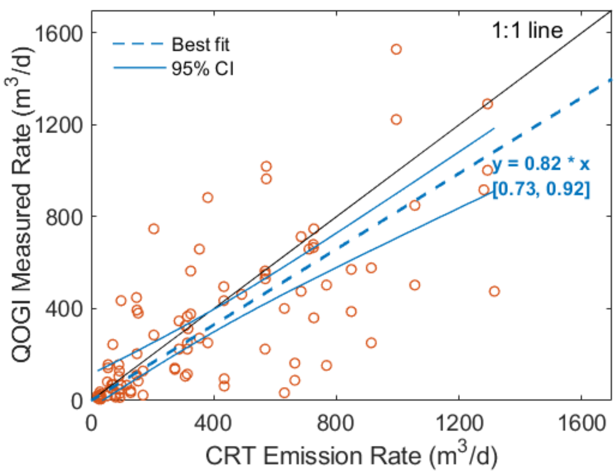


Figure 4: Parity chart of the controlled release emission rate and QOGI measured emission rate during AMFC phase 2 for both OGI teams.

The range of emission rates tested span over three orders of magnitude from about 20 scfh (13.6 m^3/d) to about 2000 scfh (1360 m^3/d) – these emission rates correspond to the low and high end of emissions typically observed at oil and gas facilities at both the component- and site-level. The CRT also reflected the relative rarity of high emitters (> 1000 scfh, 680 m^3/d) in typical field measurements, with about 80% of test rates being less than 1000 scfh (680 m^3/d). As mentioned in section 2.3, the goal of the CRT was to evaluate the quantification accuracy across a wide range of emissions rates – therefore, the rates tested here should not be assumed representative of emissions size-distributions observed at oil and gas facilities. Figure 5 shows the parity chart for CRT emission rates lower than 1000 scfh (680 m^3/d) i.e., "small rates" with a best-fit regression slope of 0.86 and a 95% confidence interval between 0.72 and 1. Because the confidence interval includes ideal parity (1), the average QOGI quantification value is statistically identical to the CRT emission rate *in the aggregate* for emission rates below 1000 scfh (680 m^3/d). The term 'aggregate' is important in the above interpretation because the slope of the best-fit regression does not correspond to any one individual measurement, but a statistical measure of the performance of QOGI.

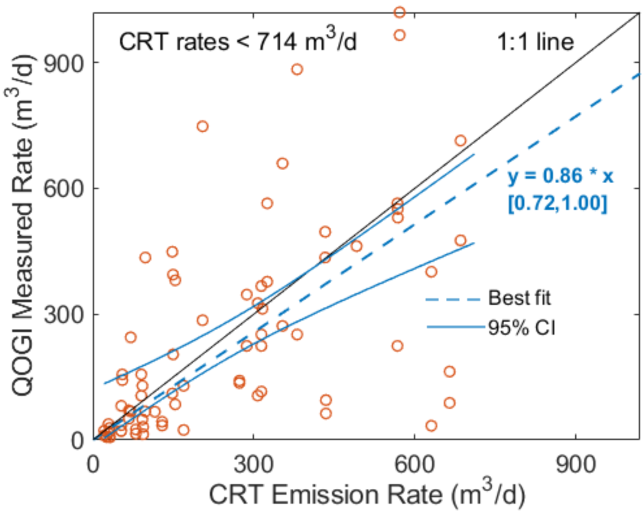


Figure 5: Parity chart of CRT emissions rate and QOGI estimated emission rate for test releases less than 1000 scfh.

3.1. The Effect of Release Height. Figure 6 shows the same CRT results of the QOGI separated by the two release heights in the measurement: 5 ft and 15 ft. We see that the measurement at 15 ft has a slope of linear regression of 0.92, and whose confidence intervals are indistinguishable from 1 – i.e., average QOGI measurements at 15 ft are identical to the controlled release rates. By contrast, measurements at 5 ft have a lower regression slope of 0.67 (95% C.I. [0.54, 0.79]), indicating some underestimation of the controlled release rate. These results are understandable based on the physics of OGI systems. Emissions at height (e.g., tank, unlit flare, separator vents, etc.) are often imaged with the sky as the background – because of the lower apparent temperature of the sky (typically, 30 to 50 degrees colder than ambient temperature), any hydrocarbon plume at ambient temperature would exhibit high contrast resulting in better detection [16]. Emissions from a lower height, on the other hand, have backgrounds that are likely to be closer to ambient temperature (e.g., other equipment) and thus provide lower imaging contrast resulting in higher uncertainty. Such differences in detection and quantification because of the effects of background has been observed in many recent field and modeling studies [10], [15], [16], [18]. While there are other factors such as distance and differential dispersion at the two heights, the apparent temperature of the background has the biggest impact on detectability [10], [31].

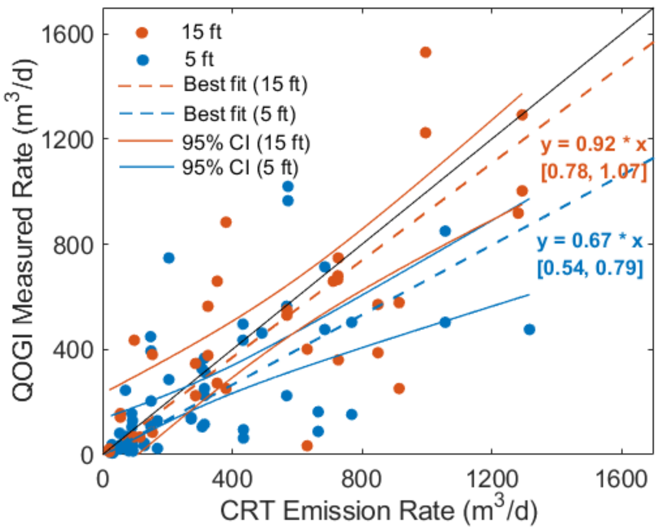


Figure 6: Parity chart of CRT emission rate and QOGI measured emission rate as a function of the height of the emission.

3.2. The Effect of Thermographer Operation. Figure 7 shows the QOGI controlled release test results separated by the two OGI field crews. For the AMFC study, the OGI team used two field crews with two personnel each. In our controlled release testing results, we find differences in the average quantification effectiveness between the two field crews. Crew 1 (team 1) data showed a regression slope of 0.89 while crew 2 (team 2) demonstrated a slope of 0.76. However, there is also significant overlap in the confidence intervals of the two field crews suggesting that the quantification from the two OGI crews might not be statistically different from each other. This is important to analyze because recent studies of multiple QOGI-based survey provides have shown that a minimum prior experience of 400 leak detection surveys is required to consistently detect methane emissions at oil and gas sites [9]. Finally, we note that the two crews did not measure CRT releases simultaneously and therefore some of the observed changes could be attributed to differences in atmospheric conditions at the time of measurement.

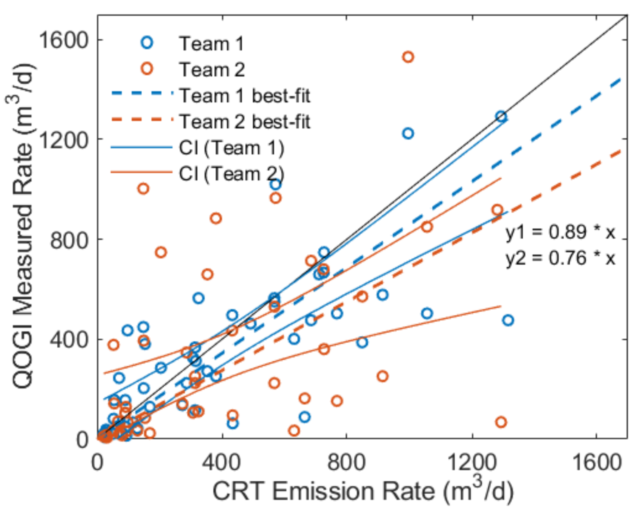


Figure 7: Parity chart of CRT emission rate and QOGI measured emission rate as a function of the two field crews that were deployed as part of the baseline OGI team in AMFC phase 2.

3.3. Individual Measurement vs. Aggregate Data: In this section, we study the role of sample size in the uncertainty of QOGI-based emissions estimates. This is important to understand the correct interpretation for QOGI data, and the difference between individual measurement errors and aggregate measurement errors.

Figure 8 shows a histogram of the **individual** errors of the QOGI emissions estimate as a percentage of the true value of the release. The errors in individual measurements span a wide range from about -90% to about +330%, with the majority of errors within the +/- 50% range. On average, the QOGI underestimates true emissions rates by 18% - these data correspond to the slope of regression line shown in Figure 5. An overall regression slope of 0.82 is equivalent to an 18% under-estimation of emissions. The individual errors in QOGI measurements have a long tail even as the average quantification across approximately 100 samples are only underestimated by 18%. This has two major implications. First, individual QOGI measurements can have high uncertainty as exhibited by the error histogram and therefore, one should not place undue emphasis on any individual data point. Second, aggregate quantification results are significantly closer to true emission rates, thus reducing overall uncertainty. Based on this information, results from QOGI surveys are best interpreted in an aggregate context, whether the site-level, site-type-level, or regional level; the larger the sample-size, the smaller the uncertainty.

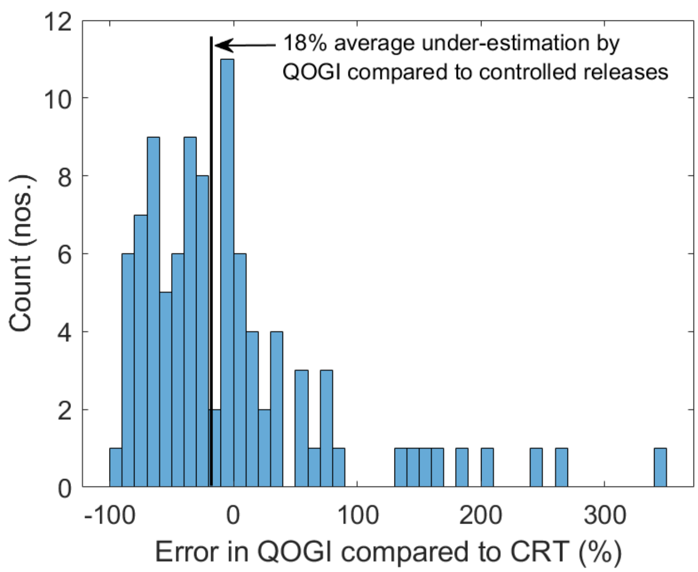


Figure 8: Histogram of the relative error (%) QOGI emissions estimate compared to the controlled releases.

If assessing QOGI data in aggregate is ideal, an assessment of how many individual data points need to be aggregated to reduce uncertainty in quantification estimates is required. To address this, we use Monte-Carlo analysis to estimate error as a function of sample size [33]. First, we generate a thousand Monte-Carlo realizations by iteratively sampling with replacement from all the CRT data (n = 97) of QOGI quantification for different sample sizes. At each iteration, the average emission of the sample is calculated, as well as the [5-95%ile] and [25-75%ile] percentile thresholds. In this way, we can estimate the expected mean and uncertainty of QOGI measurements as a function of sample size. Figure 9 plots this mean, 5-95%ile, and the 25-75%ile of Monte-Carlo simulations of QOGI estimates. Several observations can be made.

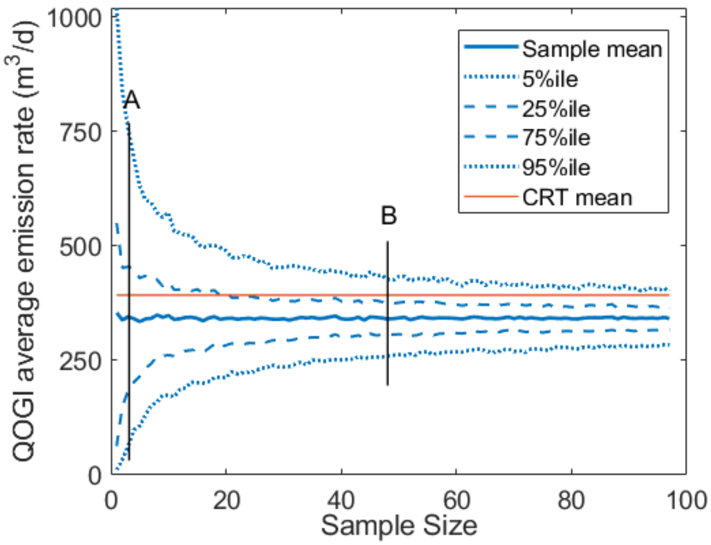


Figure 9: Monte-Carlo simulations of the uncertainty in QOGI emission estimates as a function of sample size.

First, the sample mean is approximately 18% below the CRT mean – this corresponds to the slope of the linear regression line (Figure 4) and the average measurement error (Figure 8). Second, the uncertainty range around the sample mean rapidly reduces as sample size increases. Consider two measurements – A and B – as marked in Figure 10. Measurement A consists of 5 samples, while measurement B consists of 50 samples. In measurement A, the 5th and 95th percentiles of the sample mean are 124 scfh (84 m^3/d) and 928 scfh (631 m^3/d), respectively. Thus, the average emission rate of 5 randomly chosen QOGI emissions estimate will have an uncertainty range of [-75%, +85%]. By contrast, in measurement B with 50 samples, the 5th and 95th percentiles of the sample mean are 385 scfh (262 m^3/d) and 632 scfh (430 m^3/d), respectively. Here, the average emission rate of 50 randomly chosen samples have an uncertainty range of [-23%, +26%], significantly lower than the uncertainty of the average emission rate from 5 measurement samples. Therefore, it is critically important that data from QOGI measurements – whether in this study or others – are interpreted in the aggregate context. Even increasing sample size from 5 to 20 samples reduces the uncertainty band by nearly half from [-75%, +85%] to [-34%, +39%]. This is not surprising – in an unbiased sampling of binomial trials, the uncertainty reduces as the square of the sample size. Therefore, increasing the sample size by a factor of 4 (from 5 samples to 20 samples) reduces the error by half.

The CRT measurements on QOGI provide preliminary data on uncertainty associated with QL-320 based methane emissions quantification estimates. While the study provides valuable data in understanding uncertainty estimates of QOGI, further testing is necessary to fully characterize the instrument. Therefore, we present some caveats and provide directions for potential future study:

a. Real-world emissions on oil and gas facilities are strongly influenced by local turbulence around equipment and will likely impact the accuracy of QOGI quantification estimates. The CRT tests in AMFC provided relatively ideal conditions for measurements – thus, QOGI CRT tests here are more representative of emissions from tanks or flares or other tall equipment than emissions from near-ground equipment or diffuse sources. Testing QOGI at a test-site like METEC in Fort Collins (Colorado, U.S.) will provide real-world emissions imaging conditions [28].
b. Emissions-size distributions tested in the AMFC CRT are not representative of oil and gas facilities – they were selected to represent only the range of emissions observed and the capabilities of the technologies tested.

Variations in atmospheric conditions and other weather parameters also affect QOGI measurements. Although prior research has demonstrated the impact of weather on OGI camera performance, dedicated testing of QOGI under a wider range of wind and illumination conditions are required in future studies.

Stakeholders should be careful to not directly use or interpret individual QOGI measurements. As this Monte-Carlo analysis shows, a single QOGI estimate can be uncertain by -97% or +199% in the 5th and 95th percentile, respectively, 90% of the time. The remaining 10% of the time, errors in individual measurements can be higher than the range shown here. This has importantly policy implications. Most LDAR policies in Canada (except British Columbia) do not require quantification, and all leaks that are detected by an OGI camera must be fixed, with limited exceptions. In the context of British Columbia, requiring the use of QOGI can be useful to understand both the provincial emissions inventory and the trend in methane emissions over time. The latter application would be important to evaluate the effect of methane mitigation policies. And the QOGI, despite higher individual errors, may be well-suited for aggregate measurement application – this is because uncertainty reduces as sample size increases. Therefore, while the QOGI might not be effective in estimating individual emissions at oil and gas sites, it could be an effective tool to understand aggregate emissions. We note that the CRT measurements were conducted in ideal conditions – open and isolated sources with clear background. Real-world measurements at oil and gas sites provide more complex imaging conditions and are likely to impact the performance of QOGI – future tests at facilities such as METEC in Fort Collins (Colorado, U.S.) can help understand the performance under realistic conditions.

In the context of this study as well as other prior and future studies involving QOGI-based emissions quantification estimate, we suggest the following considerations:

1. Sample size matters: Individual measurements have high uncertainty, while aggregate measurements have low uncertainty. For example, while estimates of individual emission points may have high uncertainty, QOGI-based quantification is an effective method to estimate company-wide methane emissions and annual trends. In addition, QOGI can be used to measure: (a) average emissions across sites of different site-types, (b) company-level emissions inventory estimates, and (c) annual trend of methane emissions across company (and provincial) assets.
2. Preliminary evidence suggests that the accuracy of QOGI quantification estimates are directly correlated with the effectiveness of OGI-camera based detections. For example, OGI cameras (and therefore QOGI quantification estimates) are better at detecting methane emissions under conditions of high temperature-emissivity contrast such as those seen in measurements with a clear sky background.
3. Recent studies have shown that the experience of the OGI camera operator may play a role in emissions detection, and consequently, emissions quantification using the QOGI [9]. As the use of QOGI expands in the context of Canada's methane regulations, it might be prudent to further explore the impact of operator experience in future studies.

4. Evaluation Methodology for AMFC

In the next three sections, we discuss the results of the AMFC field campaigns (phase 1 and phase 2) and compare the performance of new technologies with that of baseline QOGI survey (GF-320-based detection and QL-320-based quantification). In order to standardize performance evaluation for different technologies and deployment methods, we used a few common metrics.

4.1. Site-level Performance:

We start with a site-level summary of performance comparison between a participating team and QOGI – this comparison is conducted at the site-level for all teams, irrespective of their spatial resolution. Because some participating teams were faster than QOGI in their site survey, we define an 'overlapping sites' parameter – these are sites that the participating team and QOGI teams visited on the same day of the AMFC program following the QOGI schedule. This is to ensure that performance comparisons between OGI and participating teams correspond to emissions measured at a site on the same day. However, we caution readers that intra-day temporal variations in emissions could be a potential cause of any differences observed in the field. Using OGI as the emission detection reference, we compare the performance of participating teams with that of OGI at overlapping sites. We define four scenarios of emissions detections at the site-level:

a. OGI > 0, Tech > 0 – same detection as OGI
b. OGI = 0, Tech = 0 – same detection as OGI
c. OGI = 0, Tech > 0 – different detection from OGI
d. OGI > 0, Tech = 0 – different detection from OGI

The first scenario occurs when OGI detects emissions at a site and a same-day measurement by the participating team also detects emissions at that site (any emission, irrespective of the number of emissions). **Effectiveness** is therefore defined as the ratio of number of sites in which scenarios 'a' and 'b' occur to that of the total number of overlapping sites, i.e., the combination of correctly identified zero-emission sites and non-zero emissions sites compared to OGI. Effectiveness defined in this manner refers only to the ability of technologies to detect site-level methane emissions, not whether they will be effective in reducing emissions.

It is critical to note that effectiveness, defined in this manner, should not be construed as defining the performance of a technology. Low effectiveness can result from many causes that are unrelated to the efficacy of the technology:

a. Intra-day temporal variation of emissions at a site can result in OGI and a participating team detecting different emissions.
b. Large variation in detection limits between OGI and participating team – a high detection threshold technology will not be able to detect sites with low emissions.
c. The OGI technology is also susceptible to false positive (scenario 'b') and false negative (scenario 'c') errors and is not necessarily the ground truth in emissions.
d. Some participating teams using in-plume sensing technologies and methods could not gain downwind access of potential emissions sources to resolve emissions.

4.2. Equipment-level Performance:

For technologies that measured emissions at the equipment-level, we can estimate the detection effectiveness across equipment types. In this report, we consider six major equipment types as defined prior to the site-surveys: buildings, compressors, wellheads/pumpjacks, flares, separator/dehydrator, and tanks. These six categories were chosen to be easily visually identifiable even by participating teams with little to no experience on an oil and gas site. The purpose of the equipment-level analysis allows one to make generalized inferences about the efficacy of new technologies and platforms to detect and attribute emissions across several distinct equipment types. For example, flares and tanks provide examples of emissions high above the ground, while buildings provide examples of diffuse emission sources. For the equipment level analysis, the effectiveness is defined as the fraction of overlapping sites at which a participating team detected emissions across the six major equipment categories compared to OGI. For example, assume OGI detected emissions from tanks at 6 sites. If a participating team, overlapping with OGI at these six sites, detects emissions from tanks at 4 of the sites, the team's tank-related effectiveness would be 67% (4/6). This analysis only considers binary emissions detection (e.g., did this team detect tank emissions on site X?) and does not differentiate based on the numbers of each equipment type that may be emitting at any given site. This is important because if more than one tank at a tank battery on a site is emitting, it could present as a single large emission based on measurement method and atmospheric conditions.

There are a few isolated data points where the study team had to interpret the data reported by participating teams as the provided description did not belong to any of the major equipment-types used in this analysis. Future projects comparing multiple technologies and methods should base equipment-level detection performance on a consistent frame of reference – e.g., a plot plan, reasonably detailed site map, aerial/satellite image with labels for each site. Without such a figure, detailed comparisons may not be possible.

It is important to note that although flares have been included in this analysis because of easy identification by all participants, OGI-based imaging systems are not considered effectively at detecting and quantifying inefficient flares because of the high thermal background. Unlit flares can be easily detected by OGI.

4.3. Emissions-size Distribution:

For participating teams that quantified emissions, we can compare their emissions-size distribution with QOGI. This size-distribution is represented as a plot of the fraction of total emissions as a function of the size-ordered fraction of sites. In all cases, we only compare site-level emissions-size distribution at overlapping sites. For teams that measure emissions at the equipment-level, site-level emissions are calculated by aggregated equipment-level emissions that fall under one site. However, it is likely that such aggregation can show less skewed emissions than those measured directly at the site-level because any missed equipment-level emission reduces the overall emissions at that site. This caveat is important for QOGI and other teams that measured equipment-level emissions.

4.4. Site-Level Quantification:

For participating teams that quantified emissions, we can compare aggregated site-level emissions to that estimated by QOGI. Quantification accuracy is expressed as a parity chart of QOGI-estimated site-level emissions with that of the participating teams' site-level emissions. If the quantification measurements between QOGI and the participating team were identical, the data would plot on the 1:1 line with a linear regression slope of 1. If the regression slope is < 1, then the participating team, on average, underestimates emissions compared to QOGI. If the regression slope is > 1, then the participating team, on average, overestimates emissions compared to QOGI. In addition, we also plot the 95% confidence interval for the linear regression slope – this provides a 95% probability envelope of quantification estimates of the participating team corresponding to a given QOGI measurement. All parity charts in this report are plotted on a linear scale.

Although linear regression analysis is standard practice in the literature to analyze quantification effectiveness, it tends to weigh larger values more than smaller values. A linear regression across data spanning several orders of magnitude is challenging because minimizing the residual of the largest emission rate minimizes the total residual (i.e. the largest point gets all the weight). A few incomplete captures of large emission sources could drive a linear regression through a low value since the larger release rates will be weighted the most, i.e. the fit line will go right through the largest point, and seemingly ignore lower magnitude data. Future work can explore the use of variance weighted least square regression to analyze quantification parity.

4.5. Controlled Release Test Quantification:

In phase 2 of the AMFC program, we conducted controlled release tests for all participating teams and QOGI. Details of the CRT set-up can be found in section 2.3. Similar to the quantification analysis described above, we analyzed the results of the CRT releases using a parity chart. In this case, we are comparing methane flow rate estimates submitted by the participating teams with that of the true release rate from the controlled releases. The slope of linear regression on this parity chart gives the degree of under- or over-estimation of quantification by each team. The CRT tests designed as part of this study were not intended to be a detailed analysis of the performance characteristics of each technology. Instead, the role of the CRT tests was to estimate the quantification accuracy across a range of emission rates typically observed at oil and gas facilities.

Before presenting the results of the AMFC phase 1 and phase 2 program, we note a few caveats to the discussion.

1. The average survey speed measured in this study should not be assumed to be a proxy for expected survey speed as part of an LDAR program field deployment for at least two reasons. One, the teams collected data from sites that would be useful for analysis and comparison with OGI that might not be required as part of a typical LDAR survey. Two, because multiple teams were deployed simultaneously, there were delays when an incoming team at a site was waiting for another team on the site to finish measurement, or to coordinate site visit order based on the positions of other teams instead of an optimized survey route. In practice, one can expect survey speeds to be higher than what was demonstrated as part of this study.
2. Attribution of the differences in emissions **detection** between baseline QOGI survey and an alternative technology is a challenging problem. Without knowledge of the ground truth in emissions (since OGI survey can also have false positives and false negatives), observed differences in detection could be the result of several factors: detection errors by OGI, detection errors by the alternative technology, differences in parameters between OGI and the alternative technology, or variation in site-level emissions.
3. Differences in **quantification** between alternative technologies and QOGI can also result from several factors. These can be weather-related (wind speed, wind direction, turbulence,), survey characteristics (survey speed, air sampling location), emissions characteristics (gas composition, diffuse vs. point source), or algorithmic challenges in converting raw measurements to emission rates. Detailed controlled release test measurements should be conducted to shed light on quantification effectiveness.

Many of the technology tested in the AMFC campaign are early-stage technologies (technology readiness levels 4 – 7) and the results presented here likely represent those from initial field deployment. As such, these results should not be interpreted as being representative of the technologies as they are all likely in continuous and rapid development. This study provides valuable data for operators, regulators, and technology developers to better understand the operational challenges involved in methane emissions detection and quantification using a variety of technologies and platforms. Readers are urged to directly contact the participating technologies to get the most up-to-date performance metrics.

5. AMFC Phase 1 Results

This section will present results from AMFC phase 1. Any description of the technology used by the participating teams have been taken from teams' description of their system as part of the AMFC application process. Phase 1 of the AMFC did not include controlled release tests of any of the participating technologies – please refer to other publicly available studies (Mobile Monitoring Challenge [28], etc.) for detailed validation data on technology performance. Thus, phase 1 results from participating technologies are compared to OGI performance at overlapping sites. Because many technologies that use laser-based sensing systems have higher sensitivity than imaging-based OGI-cameras, differences in detection could arise from participating technologies identifying emissions that were not detected by the OGI camera. The better the sensitivity of participating technologies, the higher the discrepancy is likely to be.

5.1. Altus Geomatics (now GeoVerra)

Altus Geomatics team deployed a vehicle-mounted multi-gas sensing system measuring methane (CH4), δ^{13}CH4, carbon dioxide, and water vapor using cavity ring-down spectroscopy. The technology flags emitting sites and estimates emissions using a vehicle-mounted greenhouse gas analyzer, paired with GPS and meteorological measurements. The Altus' technology provides facility-level estimates of methane emissions. Altus was one of two teams that participated in both the phase 1 and phase 2 of the AMFC program.

Table 2 summarizes the performance of Altus Geomatics in phase 1 of AMFC. Overall, the team conducted 127 site surveys in 11 days, averaging about 14 sites/day. In addition, the team spent, on average, about 10 minutes on each site collecting emissions data. The average measurement time mentioned here only refers to Altus' data collection process and does not include driving time between sites. The high average speed of Altus is related to their survey protocol: Altus measured site-level emissions by driving around each site multiple times to obtain time GPS-stamped emissions measurements, which were post-processed to site-level quantification; component- and equipment-level data collection were not recorded.

Of the 127 sites visited by Altus, 40 overlapped with the OGI team. Furthermore, because the AMFC program had only 50 unique sites, Altus visited 42 of the 50 sites multiple times over 11 days, making use of the "additional available sites" – 9 sites were visited 4 separate times. Of the 40 overlapping sites, Altus identified 33 sites with emissions also detected by OGI with an average QOGI-estimated emission rate of 415 scfh (282 m^3/d), and 2 non-emitting sites that were also found non-emitting by the OGI team, for an overall site-level detection effectiveness of 87%. At the remaining 5 sites Altus' measurements indicated zero emissions while the QOGI team detected emissions. The average emission at these 5 sites estimated by QOGI was 183 scfh (124 m^3/d).

Table 2: Summary of Altus Geomatics performance in AMFC phase 1. The emission rate in parenthesis corresponds to the average QOGI-estimated emissions rate.

Altus Geomatics		**Metric**
Total number of sites visited		127
Average speed		14 sites/day
Average measurement time		10 minutes/site
Number of sites overlapping with OGI		40
	OGI > 0, Altus > 0	33 (415 scfh or 282 m^3/d)

Detection at overlapping sites	OGI = 0, Altus = 0	2
	OGI = 0, Altus > 0	0
	OGI > 0, Altus = 0	5 (183 scfh or 124 m^3/d)
Site level	Agreement with OGI	87% (35/40)
	Different from OGI	13% (5/40)

Figure 10 shows the site-level emissions-size distribution of Altus and QOGI measured in the AMFC phase 1 – this figure only includes data from sites that overlapped between Altus and OGI (n = 40). The top 10% of sites measured by the QOGI and Altus contributed to 38% and 50% of total emissions, respectively.

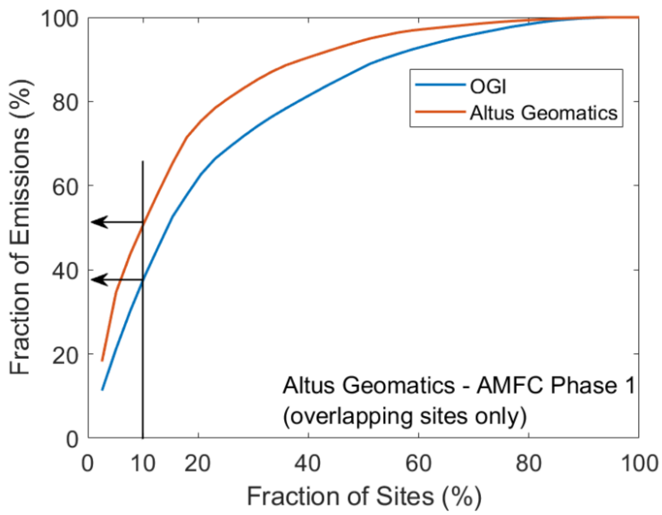


Figure 10: Site-level emissions-size distribution of Altus Geomatics and QOGI in AMFC phase 1.

Figure 11 shows the site-level emission-rate parity chart at overlapping sites (n = 40) between QOGI and Altus (zeros not shown). Altus underestimated site-level emissions compared to QOGI data. The slope of the linear regression line is 0.07, with the average site-level measurement of Altus about 83% lower than that measured by the QOGI team. There are multiple potential reasons for the underestimation including weather conditions, local turbulence, gas intake height, and challenges in close-range plume quantification. Detailed understanding of the underlying cause for underestimation of emissions would require exhaustive controlled release testing.

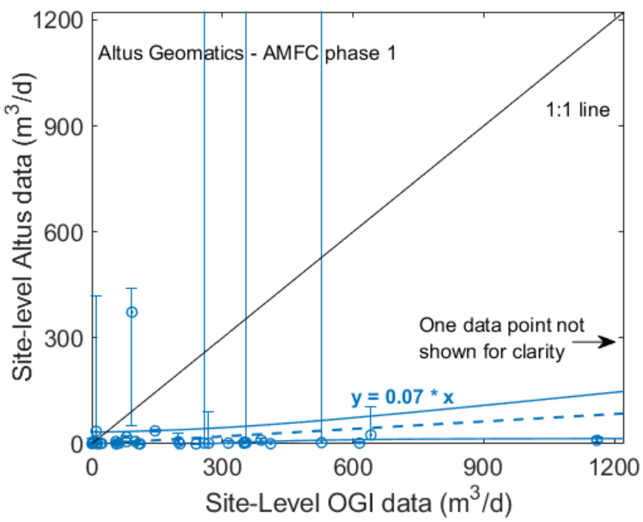


Figure 11: Site-level emissions quantification parity chart and regression coefficients between QOGI and Altus Geomatics in the AMFC phase 1 campaign. One large data point is not shown for clarity but included in the regression analysis.

Figure 12 shows the individual site-level emissions estimate comparison between QOGI and Altus in AMFC Phase 1, ranked in descending order of the average site-level emissions from all technologies. Confirming observations in the parity chart in Figure 11, Altus technologies tends to underestimate site-level emissions compared to OGI. However, the underlying data show significant variation – several sites had similar emissions estimates between OGI and Altus.

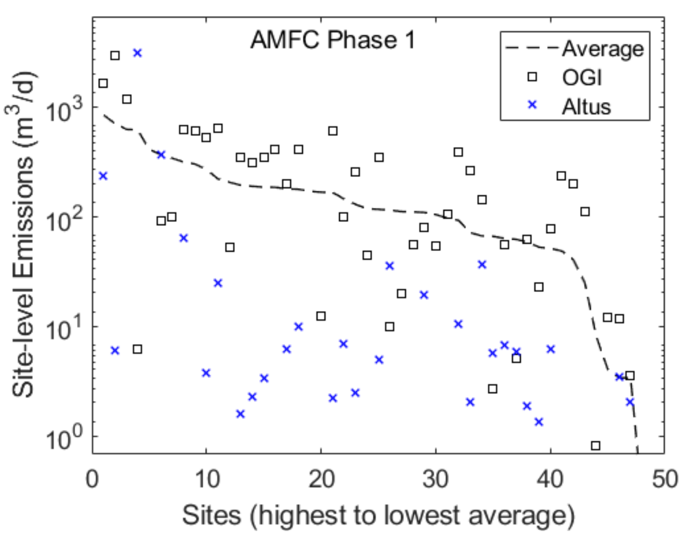


Figure 12: Site-level emissions estimate of QOGI (black squares) and Altus (blue cross) in AMFC phase 1 campaign, ranked in descending order of average site-level emissions of all technologies (black dashed line).

Altus conducted 127 site surveys over the 11 days of the AMFC campaign across 50 sites, resulting in multiple surveys of the same sites. Figure 13 shows Altus' distribution of site-level emissions measurements from the nine sites that were measured on four different days. All 9 sites emitted < 50 scfh (33 m^3/d)on average, although there was significant variation in some of the sites. Five out of 9 sites (sites A, B, E, H, and I) did not show any appreciable (standard deviation > median emissions estimate) difference in emissions across the four days, with all sites emitting < 10 scfh (7 m^3/d). One of the sites (site G) was measured to emit 250 scfh (170 m^3/d)on one of the four days, while emitting < 10 scfh (7 m^3/d) on the remaining three days. The reason for this outlier emissions is not entirely clear. The limited data in this study on repeat site measurements are insufficient to make attributional claims for observed variations in emissions. Future field studies featuring repeat site visits daily can explore underlying causes for such observations.

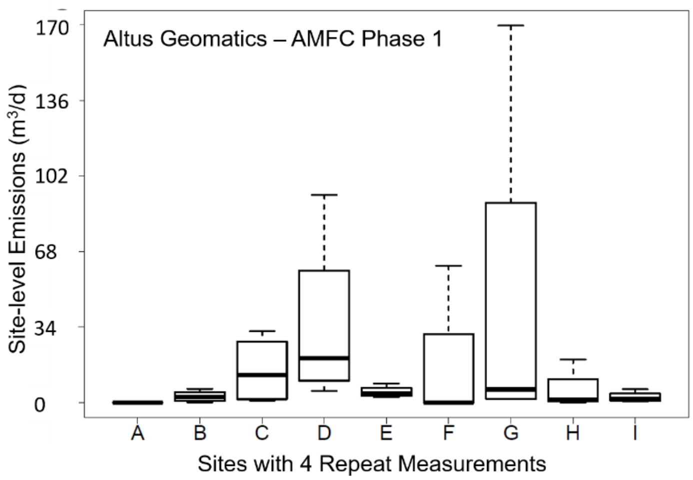


Figure 13: Average emissions measured by Altus at sites that were survey four times as part of AMFC phase 1– the four site visits happened on different days of the program.

5.2. Heath Consultants (Truck + handheld hybrid)

Heath Consultants tested a hybrid vehicle-based and handheld measurement system as part of the AMFC phase 1 program. The vehicle-based system, called the optical methane detection (OMD), uses an open-path infrared sensor based on etalon spectroscopy to detect methane emissions. Upon detection, the handheld system, called the remote methane leak detector – intrinsically safe (RMLD-IS), is used to locate the emission source. The RMLD-IS is a backscatter tunable diode laser absorption spectroscopy-based sensor that makes continuous measurements of path-integrated methane between the handheld unit and a background such as the ground or other equipment. The user manually locates the leak source and records the local path-integrated concentration. In some instances, Heath also used an ECG camera but did not report independent data from the device. In the AMFC phase 1 program, Heath provided equipment-level emissions detection data and did not quantify emission rate. Based on the organization's communications, algorithms to process raw concentration data into emission rates are under development.

Table 3 summarizes Heath's performance. Over 11 days of AMFC phase 1, Heath conducted 53 site surveys, for an average of 5 sites per day. On average, the team spent 41 minutes at each site measuring emissions – this time spent surveying includes both truck-based screening as well as handheld emissions measurements. Of the 53 sites visited by Heath, 45 overlapped with OGI on the same day. Heath identified 41 sites with emissions also detected by OGI, and 2 non-emitting sites that were also found non-emitting by the OGI team, for an overall detection effectiveness of 91%. At 4 sites, Heath detected emissions where OGI did not detect emissions. This could be because the handheld laser-based sensor typically has a higher sensitivity (parts per billion detection) than an OGI camera and thus was able to measure emissions below the resolution of OGI. Finally, there were no sites where OGI detected emissions, but Heath did not.

Table 3: Summary of Heath Consultants' performance in AMFC phase 1

Heath Consultants – Handheld + Truck hybrid		Metric
Total number of sites visited		53
Average speed		5 sites/day
Average measurement time		41 minutes/site
Number of sites overlapping with OGI		45
Detection at overlapping sites	OGI > 0, Heath > 0	41
	OGI = 0, Heath = 0	0
	OGI = 0, Heath > 0	4
	OGI > 0, Heath = 0	0
Site level	Agreement with OGI	91% (41/45)
	Different from OGI	9% (4/45)

Heath reported equipment-level detections with their handheld sensor that can be compared with OGI detections. Table 4 shows that Heath was 60-72%% effective in detecting emissions also detected by OGI across buildings, compressors, wellheads, and tanks. Flare-related emissions had the lowest detection effectiveness at 33%.

Table 4: Equipment-level comparison of emissions detection between Heath Consultants and OGI in AMFC phase 1 across six major equipment categories.

Equipment type	Heath Detect	OGI Detect	Effectiveness (%)
Building	13	18	72%
Compressor	5	8	63%
Wellhead/Pumpjack	18	30	60%
Tank	17	28	61%
Flare	3	9	33%
Separator/Dehydrator	14	33	42%

5.3. Bridger Photonics

Bridger Photonics tested a methane-only sensor mounted on a fixed-wing aircraft flying at an altitude of approximately 750 ft above ground level. The sensor captures methane concentration imaging using spatially scanned LIDAR measurements based on near-infrared (1650 nm) wavelength modulation spectroscopy. Bridger's system measures emissions both at the equipment- and site-level.

Bridger flew for 5 days out of the total 11 in AMFC phase 1. Aerial surveys can be conducted at much higher speeds than ground surveys, and in 5 days, Bridger surveyed 65 sites at an average rate of 13 sites per day, summarized in Table 5. We note that Bridger flew only between 2 – 3 hours per day, and the survey rate (sites/day) would be significantly higher for longer flight times. Furthermore, the average measurement time was 7 minutes per site – in the case of Bridger Photonics, the average measurement time includes the time it took Bridger to finish multiple passes over a given site to reduce measurement uncertainty. A single pass over a site can be completed in seconds, but performing multiple passes requires time for the aircraft to turn and return to the site. On average, between 2 to 4 passes were used for each site during the study based on the strength of the LIDAR signal from the site. Bridger identified emissions as either 'Tier 1' or 'Tier 3'. Tier 1 emissions are those emissions that were quantified and localized to a specific equipment or site. 'Tier3' emissions are observations of plumes that could neither be quantified nor localized to any specific site. In this analysis of Bridger's performance, any 'tier 3' observations at sites overlapping with OGI has been counted as zero emission detection – this is justified because it is not possible to take post-survey actions with a location for emissions. Of the 65 sites surveyed, measurements at 20 sites overlapped with OGI on the same day. Of these 20 sites, Bridger Photonics identified 6 sites with emissions at 'tier 1' that were also detected by OGI, and 1 non-emitting sites that was also found non-emitting by the OGI team, for an overall detection effectiveness of 35%. However, Bridger did not detect any 'tier 1' emissions at 12 sites where OGI detected emissions – as described previously, these correspond to 'tier 3' observations that were neither quantified not localized. This could either represent false negatives or that Bridger's detection threshold was higher than that of OGI to resolve emissions from those sites. There is some evidence for the latter. The average QOGI-estimated emission rate where Bridger identified 'tier 1' emissions was 680 scfh (462 m^3/d), while it was 157 scfh (107 m^3/d) at 'tier 3' sites. Thus, emissions at sites tagged as 'tier 3' emissions by Bridger were, on average, more than four times small than at sites tagged as 'tier 1' emissions.

Table 5: Summary of Bridger's performance in AMFC phase 1. The emission rate in parenthesis corresponds to the average QOGI-estimated emissions rate.

<table>
<tr><th colspan="2">Bridger Photonics</th><th>Metric</th></tr>
<tr><td colspan="2">Total number of sites visited</td><td>65</td></tr>
<tr><td colspan="2">Average speed</td><td>13 sites/day</td></tr>
<tr><td colspan="2">Average measurement time</td><td>7 minutes/site</td></tr>
<tr><td colspan="2">Number of sites overlapping with OGI</td><td>20</td></tr>
<tr><td rowspan="4">Detection at overlapping sites</td><td>OGI > 0, Bridger > 0 (tier 1)</td><td>6 (680 scfh or 462 m^3/d)</td></tr>
<tr><td>OGI = 0, Bridger = 0</td><td>1</td></tr>
<tr><td>OGI = 0, Bridger > 0</td><td>1</td></tr>
<tr><td>OGI > 0, Bridger = 0 (tier 3)</td><td>12 (157 scfh or 107 m^3/d)</td></tr>
<tr><td rowspan="2">Site level</td><td>Same measurement as OGI</td><td>35% (7/20)</td></tr>
<tr><td>Different from OGI</td><td>65% (13/20)</td></tr>
</table>

Bridger also reported equipment-level detections at the 6 non-zero overlapping sites where they quantified emissions across three equipment categories – buildings, tanks, and flares. Compared to OGI, Bridger demonstrated a detection effectiveness of 80% (4/5), 50% (2/4), and 50% (1/2) at buildings, tanks, and flares, respectively. Bridger did not detect emissions from compressors, wellheads, or separators where OGI found emissions. There is some ambiguity in classifying buildings and separators – while the ground OGI team differentiated between compressor buildings and separator or dehydrator buildings, Bridger reported only 'building' as the equipment category. This likely caused zero detected emissions from separators compared to OGI.

Figure 14 shows the site-level emissions-size distribution measured by Bridger and QOGI at overlapping sites (n = 8, 6 quantified sites and 2 zero-emission sites as measured by Bridger). Although there were 20 overlapping sites, Bridger was only able to quantify emissions for 8 out of the 20 sites. In the remaining 12 sites, Bridger detected indications of emissions but was not able to quantify emissions. The top 20% of sites measured by Bridger and QOGI contributed to about 56% and 59% of total emissions, respectively.

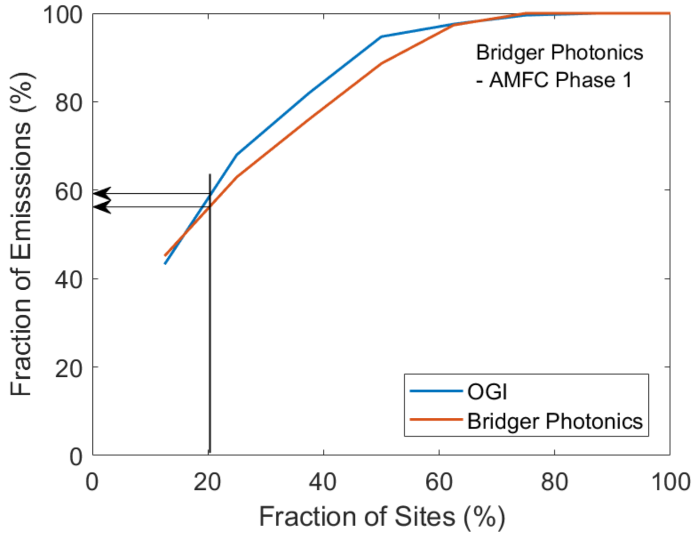


Figure 14: Site-level emissions-size distribution of Bridger Photonics and QOGI in the AMFC phase 1.

Figure 15 Figure 17: Site-level emissions quantification parity chart and regression coefficients between the University of Calgary and QOGI in the AMFC phase 1.shows the individual site-level emissions estimate comparison between QOGI and Bridger in AMFC phase 1, ranked in descending order of the average site-level emissions from all technologies. Six out of 8 sites measured by Bridger had non-zero emissions at the tier-1 level and are shown in this plot.

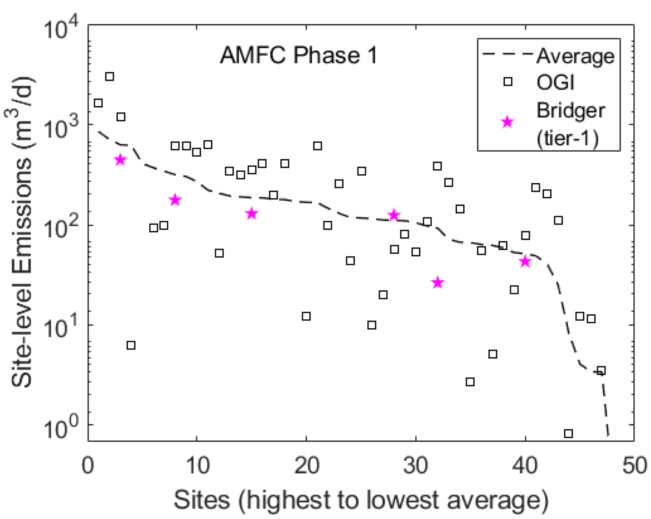


Figure 15: Site-level emissions estimate of QOGI (black squares) and Bridger Photonics (pink stars) in AMFC phase 1 campaign, ranked in descending order of average site-level emissions of all technologies (black dashed line).

5.4. University of Calgary

The University of Calgary (UofC) team employed a laser-based methane-only sensor mounted on a standard field pickup truck for equipment- and site-level emissions detection. The methane sensor uses open-path wavelength modulated spectroscopy to measure light extinction from methane absorption in the measurement path. In addition to methane, the truck is fitted with instruments such as gyros and accelerometers that measure vehicle orientation and position. The system also has an on-board anemometer to measure wind speed and wind direction. The University of Calgary team was one of two teams that participated in both the phase 1 and phase 2 of the AMFC program.

Table 6 summarizes the performance of the UofC team. Over the course of 11 days, the team surveyed 90 sites at an average survey speed of 8 sites per day. Overall, the team spent approximately 22 minutes per site. Of the 47 sites measured by UofC that overlapped with OGI, 38 sites had identical binary (yes/no) site-level emissions detection as that of OGI, for an effectiveness of 81%. Of the remaining 9 sites, UofC detected emissions at 2 sites where OGI did not detect emissions and did not detect emissions at 7 sites where OGI detected emissions. These 7 sites had an OGI-estimated average emission rate of 251 scfh (171 m^3/d). This analysis only considers whether the UofC team detected any emission at each site, not whether they detected all emissions identified by the QOGI team.

Table 6: Summary of the University of Calgary (UofC) performance in AMFC phase 1. The emission rate in parenthesis corresponds to the average QOGI-estimated emissions rate.

University of Calgary		**Metric**
Total number of sites visited		90
Average speed		8 sites/day
Average measurement time		22 minutes/site
Number of sites overlapping with OGI		47
Detection at overlapping sites	OGI > 0, UofC > 0	36 (419 scfh or 285 m^3/d)
	OGI = 0, UofC = 0	2
	OGI = 0, UofC > 0	2
	OGI > 0, UofC = 0	7 (251 scfh or 171 m^3/d)
Site level	Agreement with OGI	81% (38/47)
	Different from OGI	19% (9/47)

The UofC team also measured equipment-level emissions that can be compared with OGI equipment detections. Table 8 shows that detection agreement was 74-100% at compressors, wellheads, tanks, and separators. Detection effectiveness at building and flaring equipment showed a different pattern: 7% and 11% respectively.

Table 7: Equipment-level comparison of emissions detection between University of Calgary and OGI in the AMFC phase 1 campaign across six major equipment categories.

Equipment type	**UofC Detect**	**OGI Detect**	**Effectiveness (%)**
Building	1	15	7%
Compressor	6	6	100%
Wellhead/Pumpjack	20	27	74%
Tank	17	20	85%
Flare	1	9	11%
Separator/Dehydrator	26	29	90%

Figure 16 shows the site-level emissions-size distribution of UofC and QOGI from the AMFC phase 1 at overlapping sites. The UofC emission-size distribution is less skewed compared to that of QOGI – the top 10% of sites contributed to 46% of total emissions in the QOGI data and to about 29% of total emissions in the UofC data.

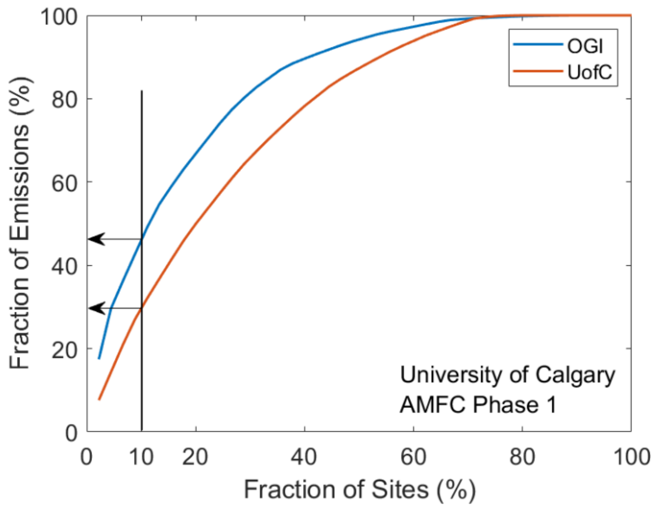


Figure 16: Site-level emissions-size distribution of University of Calgary and QOGI in the AMFC phase 1.

Figure 17 shows the parity chart for site-level quantification between UofC and QOGI at overlapping sites. The UofC team measured equipment-level emissions, and this graph was plotted by summing equipment-level emissions observed by the UofC at every site. The slope of linear regression is 0.42, indicating an average underestimation at high emission rates.

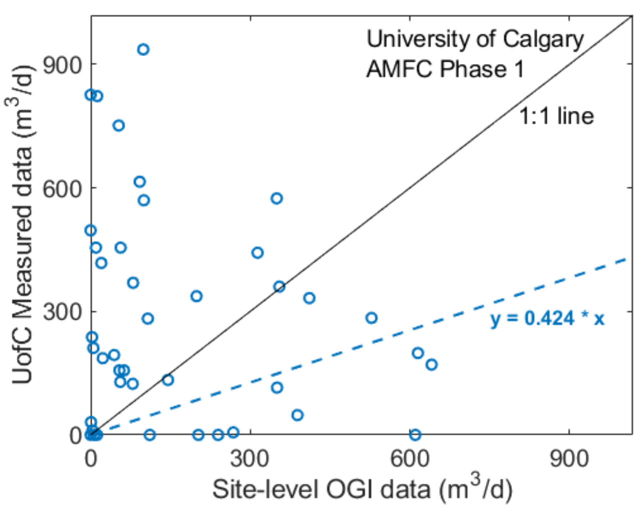


Figure 17: Site-level emissions quantification parity chart and regression coefficients between the University of Calgary and QOGI in the AMFC phase 1.

Figure 18 Figure 17: Site-level emissions quantification parity chart and regression coefficients between the University of Calgary and QOGI in the AMFC phase 1.shows the individual site-level emissions estimate comparison between QOGI and UofC in AMFC phase 1, ranked in descending order of the average site-level emissions from all technologies. The average site-level emissions as estimated by QOGI was 418 scfh (284 m^3/d), very similar to that estimated by UofC – 426 scfh (290 m^3/d).

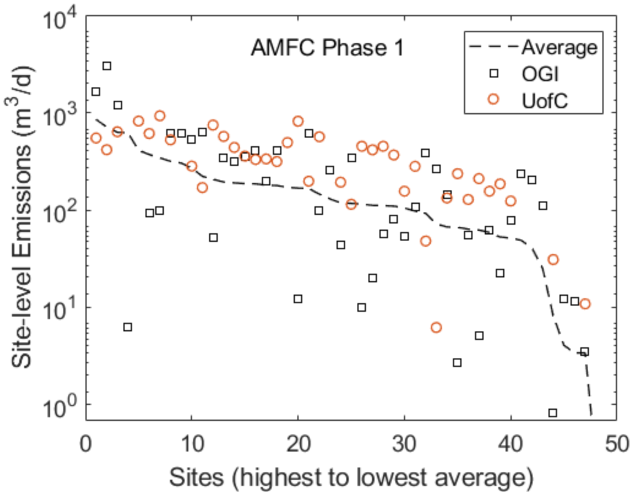


Figure 18: Site-level emissions estimate of QOGI (black squares) and University of Calgary (orange circles) in AMFC phase 1 campaign, ranked in descending order of average site-level emissions of all technologies (black dashed line).

5.5. SeekOps Inc.

SeekOps tested a methane-only, continuous, in-situ sensor based on a mid-infrared miniature methane tunable laser absorption spectrometer (SeekIR) mounted on an unmanned aerial vehicle (drone) in the AMFC phase 1 program. Typical operation for a SeekOps system includes two personnel – one pilot and one ground control operator. In some scenarios, as with AMFC, a third team member is deployed for programmatic purposes. SeekOps' technology detects, localizes, and quantifies emissions based on in-plume measurements, and reports emission rate data at the equipment-level.

In 11 days of field surveying during AMFC phase 1, Seek Ops conducted 54 site surveys, of which 38 overlapped with OGI on the same day..

Table 8 shows their overall performance. On average, SeekOps covered 5 sites/day with an average measurement time of 36 minutes per site. Of the 38 overlapping sites, SeekOps binary (yes/no) site-level emissions detection matched that of OGI at 35 sites, for an effectiveness of 92%. Of the remaining 3 sites, SeekOps detected emissions at one site where OGI did not, and OGI detected emissions at two sites where SeekOps did not detect any. The QOGI-estimated average emission rate at these two sites was 11.6 scfh (8 m^3/d).

Table 8: Summary of SeekOps' performance in the AMFC phase 1 program. The emission rate in parenthesis corresponds to the average QOGI-estimated emissions rate.

SeekOps Inc.		**Metric**
Total number of sites visited		54
Average speed		5 sites/day
Average measurement time		36 minutes/site
Number of sites overlapping with OGI		38
Detection at overlapping sites	OGI > 0, SeekOps > 0	34 (426 scfh or 290 m^3/d)
	OGI = 0, SeekOps = 0	1
	OGI = 0, SeekOps > 0	1
	OGI > 0, SeekOps = 0	2 (11.6 scfh or 8 m^3/d)
Site level	Agreement with OGI	92% (35/38)

	Different from OGI	8% (3/38)

SeekOps detected equipment-level emissions that can be compared with OGI. Table 9 shows that the detection effectiveness was 67-91% at compressors, wellheads, tanks, and separators. The SeekOps drone flew at an average lateral distance of about 10 meters (m) from the equipment, keeping to a minimum of at least 7 m as required by the facility managers. SeekOps did not detect any of 7 flare-related emissions detected by OGI and detected 3 out of 15 emissions from buildings detected by OGI.

Table 9: Equipment-level comparison of emissions detection between SeekOps and OGI in the AMFC phase 1 campaign across six major equipment categories.

Equipment type	SeekOps Detect	OGI Detect	Effectiveness (%)
Building	3	15	20%
Compressor	4	6	67%
Wellhead/Pumpjack	20	22	91%
Tank	21	23	91%
Flare	0	7	0%
Separator/Dehydrator	23	26	88%

Figure 19 shows the emission-size distribution measured by SeekOps and QOGI at overlapping sites (n = 38). The top 10% of sites measured by SeekOps and QOGI contribute to about 70% and 44% of total emissions, respectively. While component-level emissions data are available for OGI, it is not directly comparable to the equipment-level emissions detected by SeekOps from the perspective of leak-size distribution – this is because skewness reduces with increasing aggregation.

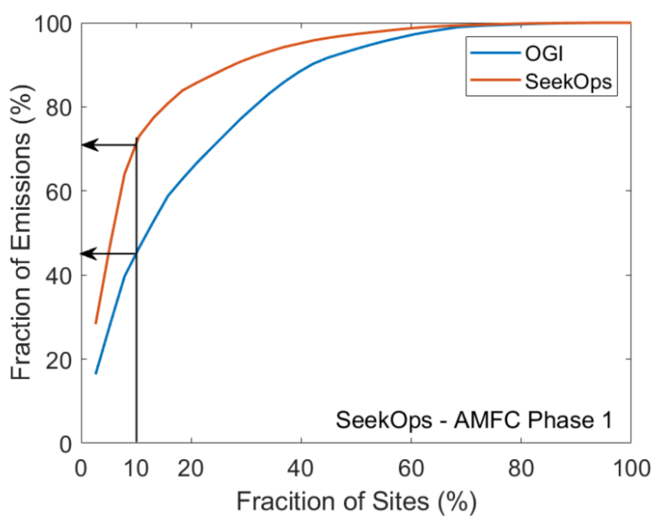


Figure 19: Site-level emissions-size distribution of SeekOps and QOGI in the AMFC phase 1.

Figure 20 shows the site-level emissions rate parity chart at overlapping sites between QOGI and SeekOps. The slope of linear regression is 0.1, indicating an order of magnitude lower quantification compared to OGI, on average. We note that SeekOps performs significantly better at sites where OGI measured site-level emissions lower than 500 scfh, that had a regression slope of about 0.4, while underestimating large emitting-sites.

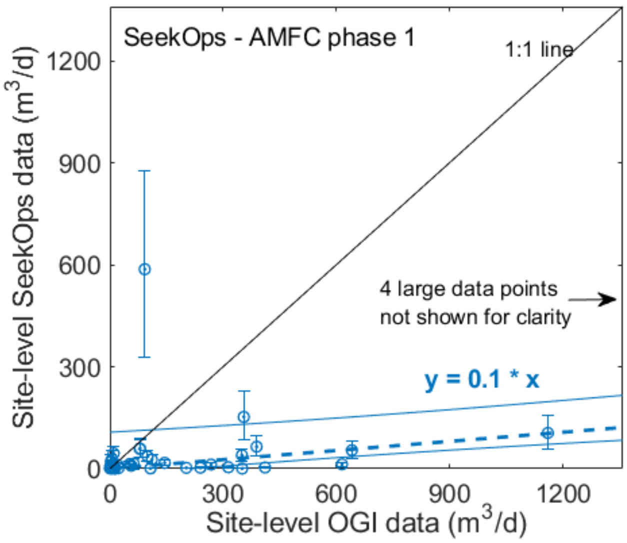


Figure 20: Site-level emissions quantification parity chart and regression coefficients between the SeekOps and QOGI in the AMFC phase 1. Four large data points are not shown for clarity but included in regression analysis.

Figure 21 shows the individual site-level emissions estimate comparison between QOGI and SeekOps in AMFC phase 1, ranked in descending order of the average site-level emissions from all technologies. Although the average emissions estimated by SeekOps is lower than that of QOGI, several sites have similar quantification estimates.

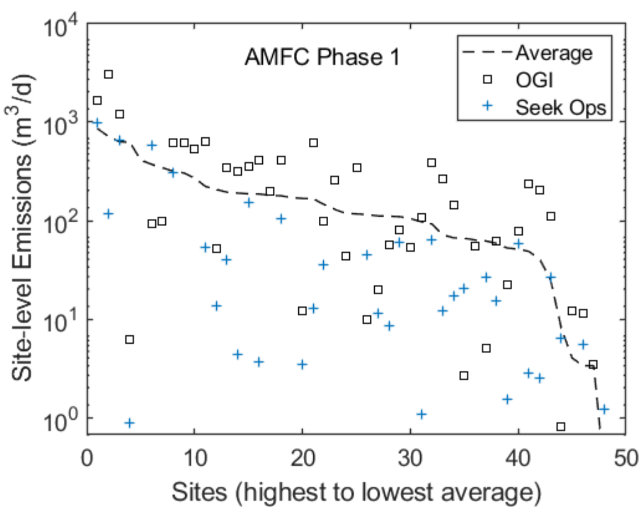


Figure 21: Site-level emissions estimate of QOGI (black squares) and SeekOps (blue plus sign) in AMFC phase 1 campaign, ranked in descending order of average site-level emissions of all technologies (black dashed line).

5.6. Aerometrix Inc.

Aerometrix Inc. tested a miniature tunable mid-infrared open-path laser spectrometer mounted to an unmanned aerial vehicle (drone) as part of the AMFC phase 1 program. The sensor measured methane, ethane, and carbon dioxide concentrations at a fixed 10 Hz data collection rate. In addition to trace gases, the platform is fitted with instruments like an anemometer that measures wind velocity, and temperature and pressure sensors. In the AMFC phase-1 program, Aerometrix reported methane emission rates at the equipment-level.

Table 10 shows the performance summary for Aerometrix. Over the course of 9 days in the AMFC phase 1 program, Aerometrix conducted 44 site surveys with an average of 5 sites per day. The Aerometrix team were not able to start on the first day of measurement (June 11th) and instead started on June 13th, resulting in 8 days of surveys. On average, the Aerometrix team spent 21 minutes per site detecting and measuring emissions, not including time for set-up and take-down after measurements. Of the 44 sites measured by Aerometrix, 29 overlapped with OGI on the same day. For these overlapping sites, Aerometrix achieved an effectiveness rate of 79% compared to QOGI measurements, Of the 21% mismatch, Aerometrix detected emissions at 2 sites where OGI did not detect emissions and did not detect emissions at 4 sites where OGI detected emissions.

Table 10: Summary of Aerometrix's performance in AMFC phase 1. The emission rate in parenthesis corresponds to the average QOGI-estimated emissions rate.

Aerometrix – Performance Summary		**Metric**
Total number of sites visited		44
Average speed		5 sites/day
Average measurement time		21 minutes/site
Number of sites overlapping with OGI		29
Detection at overlapping sites	OGI > 0, Aerometrix > 0	23 (390 scfh or 265 m^3/d)
	OGI = 0, Aerometrix = 0	0
	OGI = 0, Aerometrix > 0	2
	OGI > 0, Aerometrix = 0	4 (316 scfh or 215 m^3/d)
Site level	as Agreement with OGI	79% (23/29)
	Different from OGI	21% (6/29)

Aerometrix also measured equipment-level emissions at sites where emissions from specific equipment could be reasonably isolated. Table 11 shows the detection effectiveness across 6 major equipment types at sites where Aerometrix and OGI overlapped. Emissions at wellheads, tanks and buildings detected by Aerometrix matched with that of OGI across at least 70% of the sites. Notably, Aerometrix had a high success rate in identifying building emissions (80%).

Table 11: Equipment-level comparison of emissions detection between Aerometrix and OGI in AMFC phase 1 across six major equipment categories.

Equipment type	**Aerometrix Detect**	**OGI Detect**	**Effectiveness (%)**
Building	8	10	80%
Compressor	3	5	60%
Wellhead	10	14	71%
Tank	12	17	71%
Flare	2	5	40%
Separator/Dehydrator	0	19	0%

Figure 22 shows the site-level emission size distribution measured by QOGI and Aerometrix at overlapping sites (n = 29). The top 10% of emitting sites detected by QOGI and Aerometrix team contribute to 44% and 62% of total emissions, respectively.

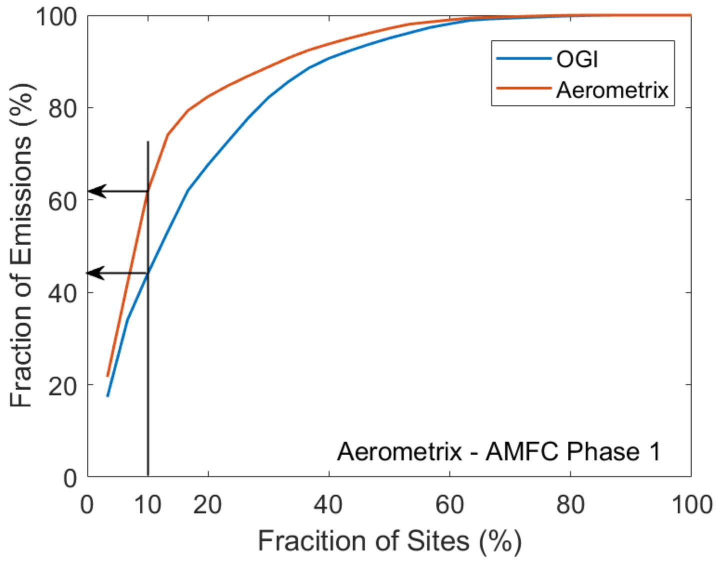


Figure 22: Site-level emissions-size distribution of Aerometrix and QOGI in AMFC phase 1.

Figure 23 shows the site-level quantification parity chart between QOGI and Aerometrix at the 29 sites where they overlapped on the same day. Compared to QOGI, the slope of linear regression was only 0.03 for Aerometrix, over an order of magnitude lower than QOGI.

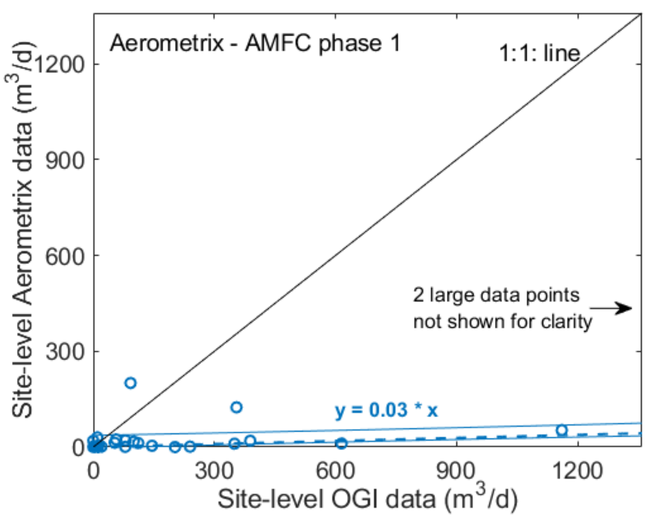


Figure 23: Site-level emissions quantification parity chart and regression coefficients between Aerometrix and QOGI in AMFC phase 1. Two large data points are not shown for clarity but included in the regression analysis.

Figure 24 shows the individual site-level emissions estimate comparison between QOGI and Aerometrix in AMFC phase 1, ranked in descending order of the average site-level emissions from all technologies.

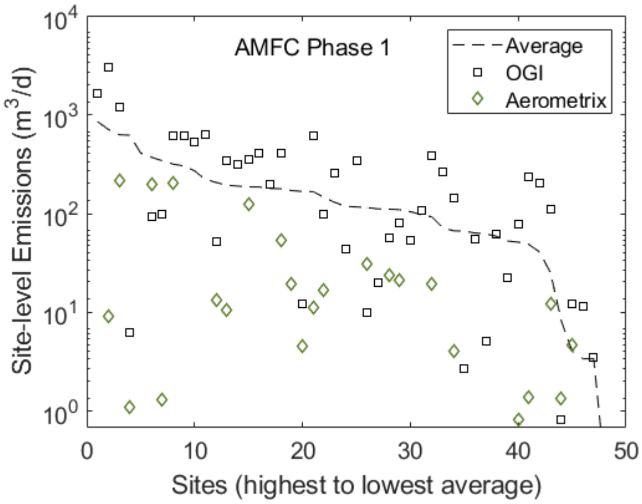
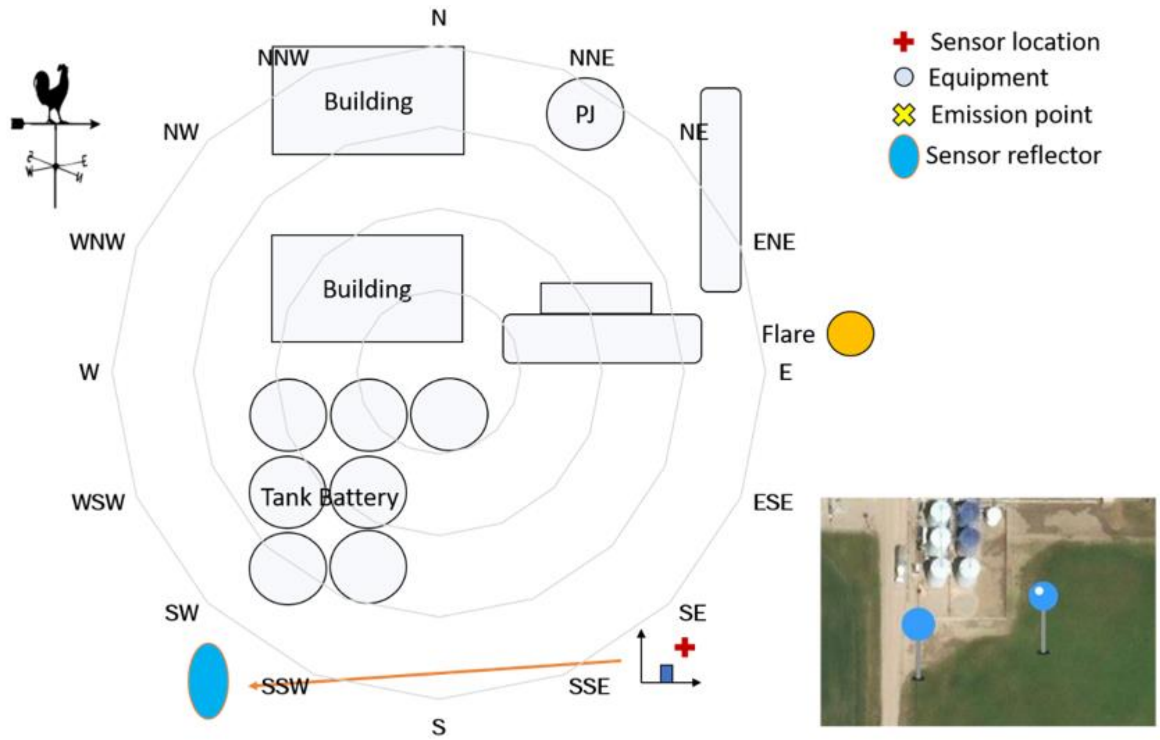


Figure 24: Site-level emissions estimate of QOGI (black squares) and Aerometrix (green diamonds) in AMFC phase 1 campaign, ranked in descending order of average site-level emissions of all technologies (black dashed line).

5.7. Heath Consultants – Fixed Sensor

Heath Consultants installed a fixed sensor on one of the sites in June of 2019 during AMFC phase 1. The sensor remained on-site, collecting data, until December 2019. The technology is a fixed, continuous-operating solar-powered long open-path sensor based on backscatter tunable diode laser absorption spectroscopy that monitors methane emissions across a line of sight. The backscatter target of the open-path sensor was installed approximately 22 meters (m) away from the optical transceiver. The sensor measured path-integrated methane between the transceiver and backscatter target at a temporal resolution of 100 milliseconds – however, data is stored to the cloud every 6 seconds. A schematic of the site, along with the location of the fixed sensor and the backscatter target, is shown in Figure 25.



Path Length: 22 m Direction from sensor to reflector: SW 230º, direction reflector to Sensor: 70°

Figure 25: Schematic of the site and the location of the Heath Consultants' fixed sensor deployed in AMFC phase 1.

The fixed sensor technology recorded data continuously with information on methane concentration path-length, wind speed, and wind direction. The concentration path-length refers to path integrated methane concentrations between the laser source and the backscatter target – for example, a background methane concentration of 1.8 ppm across a 22 m path length will record a concentration path length of 40 ppm-m. Data collected were automatically and remotely uploaded to the cloud for the science team's use. While real-time data is a typical features of a continuous methane sensor, a leak detection and repair solution for the oil and gas industry requires that the raw methane concentration pathlength data be converted to information on leak locations, leak rate, and whether the observed emission corresponds to a leak or a vent. These attributes result in markedly different and unique analyses being required for fixed sensors, like the one deployed in AMFC phase 1, in comparison to mobile methane detection platforms described in previous sections of this report. The raw data from the fixed sensor was concentration-path length over time, in addition to wind-related parameters. The science team used these raw data to convert it into meaningful information about site-level emissions that are described below.

Figure 26 shows that interface provided by Heath that is continuously updated with data from the sensor – it gives the methane concentration path-length between the location of the source lasers and the backscatter target on the site (see Figure 25) as a function of time. The sensor also measures and reports real-time windspeed and wind direction information. Using the schematic above and correlating methane concentration data with wind information, the timing and location of methane emissions on site can be estimated. Quantified emission rates are not an output of the interface.

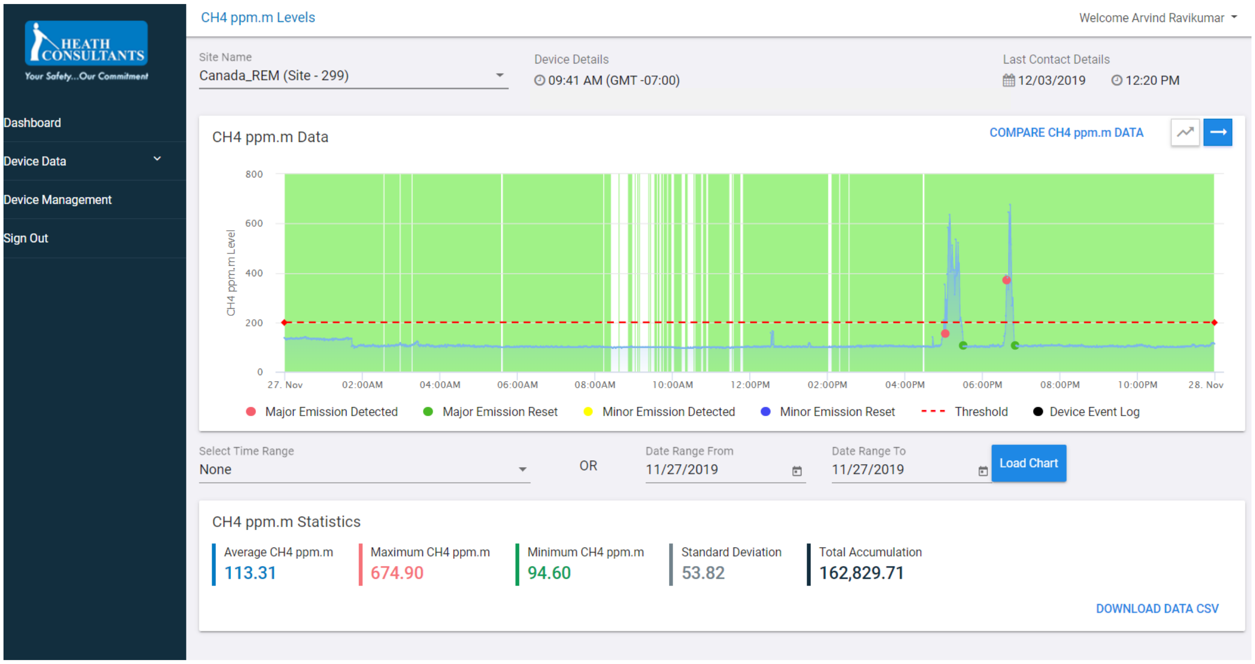


Figure 26: A screenshot of the user interface of the Heath Consultants' fixed sensor that transmits real-time, temporally resolved data on methane concentration path-length, wind speed, and wind direction.

To provide an example of the methodology, one day's worth of data was used to convert the methane concentration path-length data as a function of time to a function of wind direction as shown in Figure 27. This shows data aggregated over the course of 24 hours and collected at 10-minute intervals. A few important insights can be gained from this analysis.

Firstly, the raw concentration vs. time data was converted to concentration vs. wind direction data. Indications of high methane enhancements above background were observed at about 5, 33, and 56 degrees from North. This indicates that on this day, methane was being emitted from a specific direction and therefore, a specific source, or cluster of sources. Knowing the approximate position of various potential emission sources at the site aids in attributing the methane enhancement to a piece of equipment or an equipment group. For example, the broad peak around 56 degrees (~11° full width at half maximum) is coming from a possibly unlit flare stack on the site, while the two sharp peaks are likely coming from the tank batteries.

Secondly, two of the three methane enhancements observed in this graph are narrow (< 1° width), while the third, at approximately 56 degrees, is broader (~11° full width at half maximum). This is indicative of the distance of the source from the sensor – this can help differentiate point sources that could be co-linear with the wind direction. Sharp peaks occur when the source of the emission is close to the sensor, and broader peaks occur when the source is farther from the sensor. This is because a plume from sources close to the sensor tends to be narrow when it reaches the sensor pathlength, as they do not have as much time to disperse before the sensor detects the increased concentration, and even minor changes in wind direction will make the emission appear as distinct peaks at different angles. Plumes from sources farther from the sensor have time to disperse before it reaches the sensor; in this scenario, slight changes in wind direction would only seek to "smear" the wide plume away from its central location, resulting in a broader peak as opposed to a narrow one. Another potential explanation for the occurrence of broad peaks are near-sensor diffuse emission sources; however, it is unlikely that a diffuse emission source would produce 4 ppm enhancement relative to background concentrations.

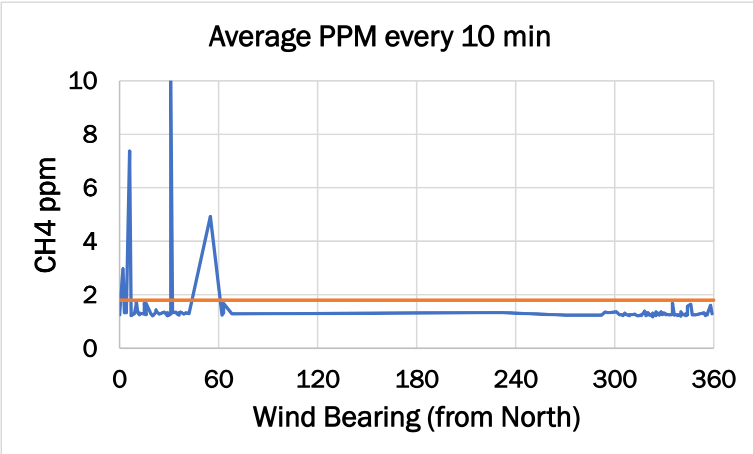


Figure 27: Conversion of the raw concentration-path length as a function of time data provided by Heath into methane concentration enhancements as a function of wind direction.

These data can be further analyzed by exploring the temporal behavior of methane enhancements. Figure 28 plots the same information in Figure 27, above, but with time on the z-axis in intervals of 30 minutes, over a 24-hour period. This kind of visualization enables an understanding of the temporal variability of methane emissions from oil and gas facilities. This plot shows that the emissions identified above at 5, 33, and 56 degrees are not continuous, but intermittent emissions. It also shows that all three emissions occurred between 4 PM and 8 PM – incidentally, this provides anecdotal confirmation of a recent paper that suggested that differences between aerial and ground-based methane emissions can be attributed to the afternoon timing of most flights when emissions occur [34]. This is critical information in the context of LDAR surveys – periodic measurements will likely miss any such emissions if the survey is not conducted at the same time as the emissions occur. However, having a fixed sensor continuously monitor the site can help operators identify anomalous but one-time emissions and undertake appropriate repairs.

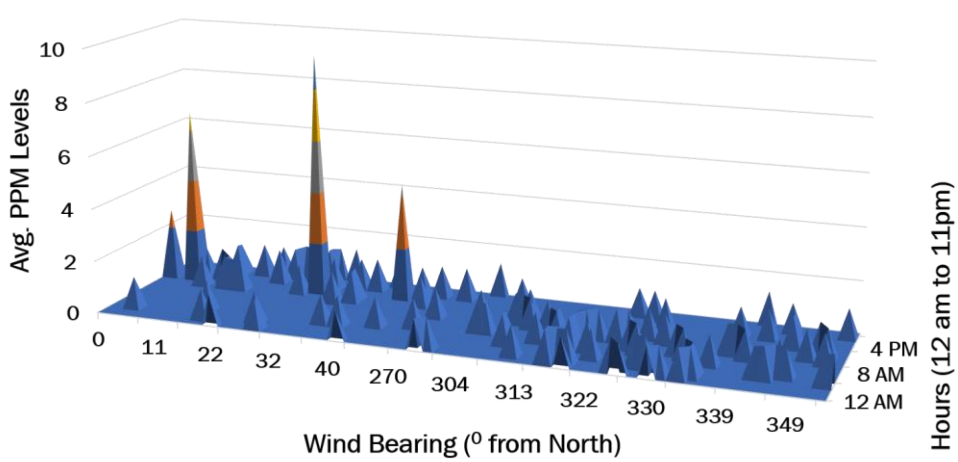


Figure 28: Temporally resolved methane enhancements as a function of wind direction as measured by the Heath Consultants' fixed sensor – the analysis presented here was conducted by the study team and not provided by the participating team.

Notably, the analysis of Heath's results was undertaken by the study team and not provided by Heath. The analysis presented here demonstrates the potential advantages of fixed sensors in identifying intermittent methane emissions at oil and gas sites and provide timely feedback to site operators to undertake corrective action. However, this requires that companies developing fixed sensors also need to provide a robust analytical platform that converts the raw data collected by the sensor into useful information.

6. AMFC Phase 2 Results

AMFC phase 2 was conducted between November 13 – 24, 2019, generally using the same sites selected for phase 1. The following changes to field and data collection methods-and drivers were made between phase 1 and phase 2:

- 5 sites included in phase 1 were replaced with 5 new sites in phase 2. The sites removed from the program had challenging logistical issues, had been shut-in or had a high probability of being shut-in during the planning stages of phase 2.
- The study team standardized the definition for the survey time data collected from teams. Participating teams were given strict definitions of how survey time data was to be collected and would be used. The result is that for teams that participated in both phases, the survey time is not comparable between the two phases.
- Minor changes and updates were made to schedule, workflow and management procedures based on learnings from phase 1. Except for the addition of controlled release testing (described below) these changes were minor.
- Controlled release testing, described in Section 2.3, was added to the program in phase 2. This significantly changed the workflow for participating teams, with the added requirement of visiting the controlled release site each day. This reduced any given team's ability to optimize route planning on each day of the program, and time spent conducting controlled release testing represents time not spent conducting surveys. Overall, this was an experimental condition that reduced the number of site surveys that could be conducted per day.
- Two teams (FLIR and Tecvalco) only participated for half of phase 2 (5 days each) for logistical reasons. All other teams participated for the full 11 days.

Except for the addition of controlled release testing, survey methodologies and workflow procedures for OGI and the participating teams were not changed significantly. Here, we will discuss the performance of participating teams in the context of site surveys as well as controlled release testing.

Note on survey speed in AMFC Phase 2: In general, for teams that participated in both phases of the AMFC program, the average survey speed (sites per day) is likely to be lower in AMFC phase 2 than in phase 1. There are multiple potential reasons for this: one, winter driving conditions increases travel time; two, mandatory controlled release testing reduced the amount of time available for site surveys; and three, reduced daylight hours during which to conduct a survey compared to June. It is likely that the most significant factor in the reduction of sites per day is the introduction of the controlled release testing.

The analysis of the performance of teams in the AMFC phase 2 was identical to that of phase 1 and can be found in section 4. In addition, phase 2 also included limited controlled release tests of all participating teams – these are discussed separately for each team. Methodological detail about the controlled release tests can be found in section 2.3. Because of the limited nature of the CRT tests, they are only used to assess the quantification accuracy of the technologies and not to derive leak detection probability curves.

6.1. Altus Geomatics (now GeoVerra)

Altus Geomatics was one of two participating teams that participated in both phase 1 and 2 of AMFC. A description of their methodology can be found in Section 5.1.

A summary of Altus' performance is shown in Table 13. Over 11 days, Altus conducted 90 site surveys, of which 47 overlapped with OGI. The average survey speed was approximately 8 sites per day, with the team spending an average of 5 minutes on each site. Altus identified 43 sites with emissions also detected by OGI, and 1 non-emitting site that was also found non-emitting by the QOGI team, for an overall site-level detection effectiveness of 94%. At the remaining 3 sites, Altus detected emissions at 1 site where OGI did not detect emissions, and Altus did not detect emission at 2 sites where OGI detected emissions.

Table 12: Summary of Altus Geomatics' performance in AMFC phase 2. The emission rate in parenthesis corresponds to the average QOGI-estimated emissions rate.

Altus Geomatics – AMFC phase 2		**Metric**
Total number of sites visited		90
Average speed		8 sites/day
Average measurement time		5 minutes/site
Number of sites overlapping with OGI		47
Detection at overlapping sites	OGI > 0, Altus > 0	43 (214 scfh or 145 m^3/d)
	OGI = 0, Altus = 0	1
	OGI = 0, Altus > 0	1
	OGI > 0, Altus = 0	2 (114 scfh or 78 m^3/d)
Site level	as Agreement with OGI	94% (44/47)
	Different from OGI	6% (3/47)

The emission size-distribution for Altus' and QOGI measurements in AMFC phase 2 is shown in Figure 29, at overlapping sites. The top 10% of sites from the OGI and Altus teams contribute to 37% and 50% of total emissions, respectively.

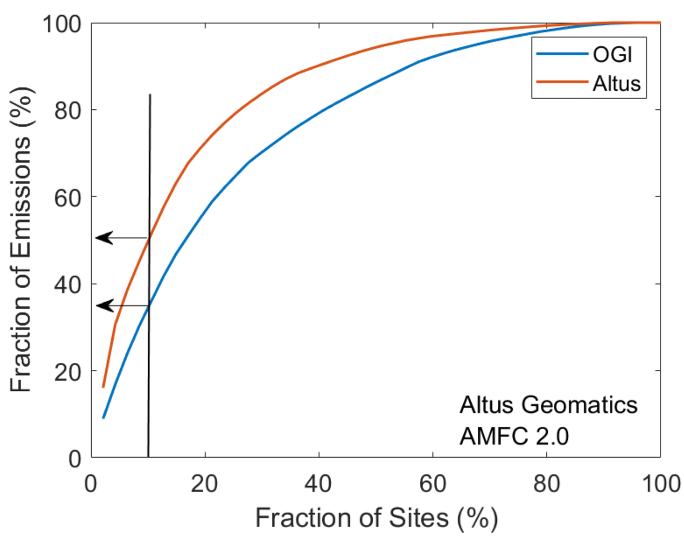


Figure 29. Site-level emissions-size distribution of Altus Geomatics and QOGI in AMFC phase 2.

The results of Altus' CRT in AMFC phase 2 are shown in Figure 30. 54 independent controlled releases were tested with Altus; 32 were emissions at 5 feet and 22 were at 15 feet. Overall, Altus tended to underestimate emissions, with a linear regression slope of about 0.2. However, there was a difference in the quantification accuracy at the two release heights: 5 feet and 15 feet. The slope of linear regression at test heights of 5 ft and 15 ft is 0.41 and 0.05, respectively. This suggests that Altus is more accurately able to quantify emissions closer to the ground (~ 5 feet) than emissions at height. This has important implications for detecting and quantifying emissions at height on operating facilities, such as tanks and flares. Emissions from tanks at height often disperse directly upwards into the atmosphere under favorable conditions, potentially missing the sample collection intake of a truck-based sensor. In this scenario, the plume centerline may not be captured by the sensor resulting in significant underestimation. Recent studies have attempted to map the two dimensional plume surface using multiple intake locations on a truck-based system [35]. Given that the 95% confidence interval for releases at 15 ft lie entirely within the 95% confidence interval for releases at 5 ft, the difference observed here may not be statistically significant. Future tests with increased sample sizes can further test quantification accuracy as a function of release height.

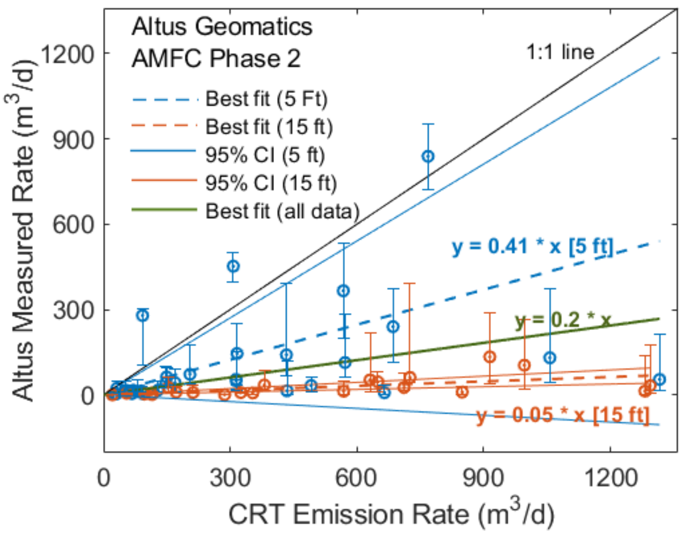


Figure 30: Parity chart of controlled releases conducted at the CRT site of Altus Geomatics' in AMFC phase 2.

Figure 31 shows the quantification parity chart between Altus and QOGI at overlapping sites in AMFC phase 2. The slope of the regression line is 0.24, indicating an average underestimation of site-level emissions. One potential cause for this underestimation can be understood from the CRT tests – Altus tends to underestimate emissions from greater heights, thus resulting in lower overall emissions estimates. The slope of the regression in the parity chart from phase 2 has significantly improved for Altus technologies compared to their performance in phase 1 (0.24 vs. 0.07), indicating that there may be potential opportunities to improve quantification algorithms.

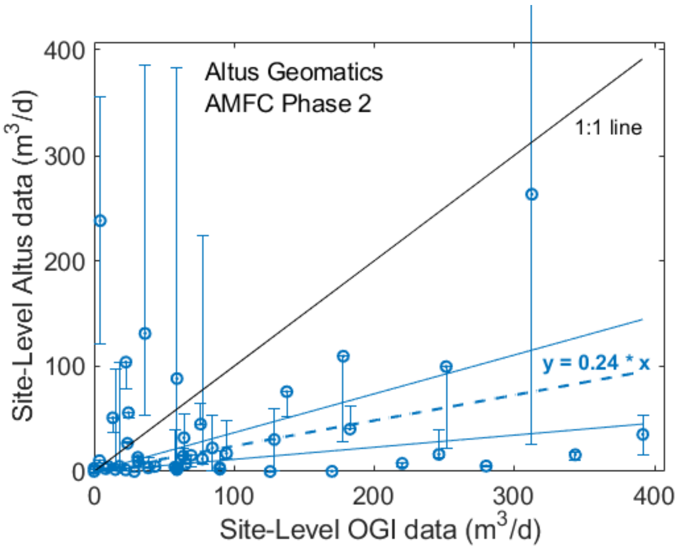


Figure 31: Site-level emissions quantification parity chart and regression coefficients between Altus Geomatics' and QOGI in AMFC phase 2.

Figure 32 shows the site-level quantification estimates of Altus Geomatics in comparison with that of QOGI in both AMFC phase 1 and phase 2 campaigns for comparison. In both cases, Altus, on average, underestimates site-level emission rate compared to QOGI. However, there is significant variation across sites, with several sites showing similar quantification estimates between QOGI and Altus. Future studies involving continuous site-level emissions monitoring systems could help untangle quantification errors from temporal variations in site-level emissions. Overall, average site-level emissions also reduced in phase 2 compared to phase 1 by 48% and 61% for QOGI and Altus Geomatics, respectively.

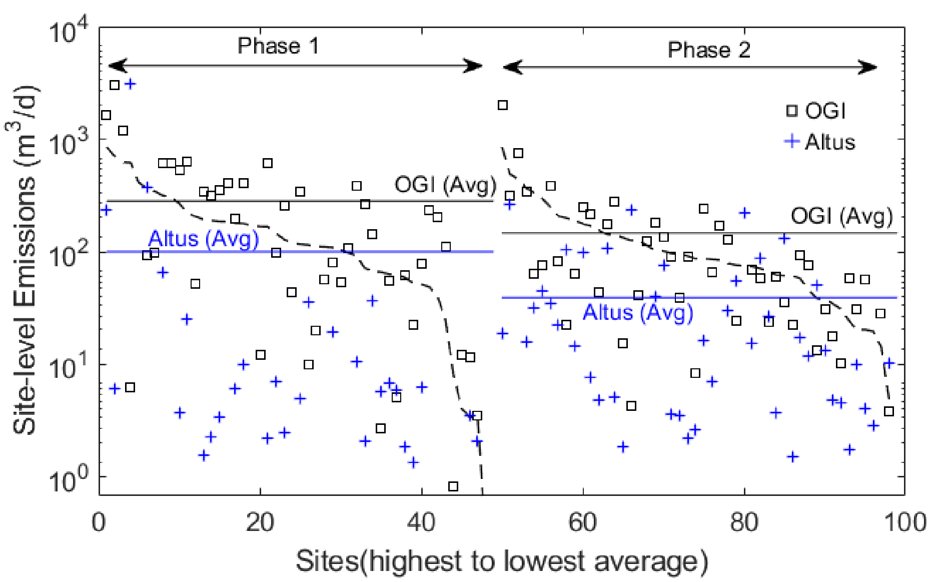


Figure 32: Site-level emissions estimate of QOGI (black squares) and Altus Geomatics (blue plus sign) in AMFC phase 1 (left) and phase 2 (right) campaigns, ranked in descending order of average site-level emissions of all technologies (black dashed line). Both phase 1 and phase 2 here are shown for comparison. The average quantification estimates in each of the AMFC campaigns for QOGI (solid black line) and Altus (solid blue line) are also shown.

6.2. University of Calgary

The University of Calgary was one of two teams that participated in both phase 1 and 2 of AMFC. A description of their methodology can be found in Section 5.4. Table 13 summarizes the performance of UofC in AMFC phase 2. The UofC team conducted 54 site surveys at an average speed of 5 sites per day. The average site survey time was approximately 6 minutes. UofC identified 36 sites with emissions also detected by OGI, and 1 non-emitting site that was also found non-emitting by the OGI team, for an overall site-level detection effectiveness of 94%. Of the remaining 4 sites, UofC detected emissions at 3 sites where OGI did not detect emissions, and 1 site where UofC did not detect emissions where OGI detected emissions. Coincidentally, the average emission rate at sites where UofC correctly detected emissions and incorrectly did not detect any emissions was 151 scfh (103 m^3/d) – this is because of one large emitting site (363 scfh, 246 m^3/d) identified by OGI that was not detected by UofC.

Table 13: Summary of University of Calgary (UofC) performance in the AMFC phase 2 campaign. The emission rate in parenthesis corresponds to the average QOGI-estimated emissions rate.

University of Calgary (UofC) – AMFC phase 2		**Metric**
Total number of sites visited		54
Average speed		5 sites/day
Average measurement time		6 minutes/site
Number of sites overlapping with OGI		41
Detection at overlapping sites	OGI > 0, UofC > 0	36 (151 scfh or 103 m^3/d)
	OGI = 0, UofC = 0	1
	OGI = 0, UofC > 0	1
	OGI > 0, UofC = 0	3 (151 scfh or 103 m^3/d)
Site level	Agreement with OGI	90% (37/41)
	Different from OGI	10% (4/41)

In addition to site-level data, UofC also measured equipment-level emissions. Table 14 shows the comparison between UofC and QOGI across six major equipment types. The UofC team detected 60-88% of equipment-level emissions detected by QOGI at compressors, tanks, flares, and separators. The detection effectiveness for emissions from buildings and well-heads were 53% and 50%, respectively.

Table 14: Equipment-level comparison of emissions detection between University of Calgary and OGI in AMFC phase 2 campaign across six major equipment categories.

Equipment type	**UofC Detect**	**OGI Detect**	**Effectiveness (%)**
Building	18	34	53%
Compressor	7	8	88%
Wellhead	7	14	50%
Tank	12	20	60%
Flare	2	3	67%
Separator/Dehydrator	26	30	87%

The results of UofC CRT in AMFC phase 2 are shown in Figure 33. In addition to collecting emissions data, the UofC team also set up on-site to measure wind speed and wind direction data. Overall, the UofC team was evaluated across 49 independent controlled releases, of which 28 were at 5 feet and 21 were at 15 feet. The slope of linear regression is 1.35, indicating a 35% overestimation of emissions, on average. Disaggregating these data across the two release heights, we find that the over-estimation was higher for releases at 5 feet (regression slope of 1.64) compared to releases at 15 feet (regression slope of 1.17).

Given the significant overlap between the 95% confidence intervals of the 5 feet and 15 feet releases, the difference observed here may not be statistically significant. Future tests with increased sample sizes can further test quantification accuracy as a function of release height.

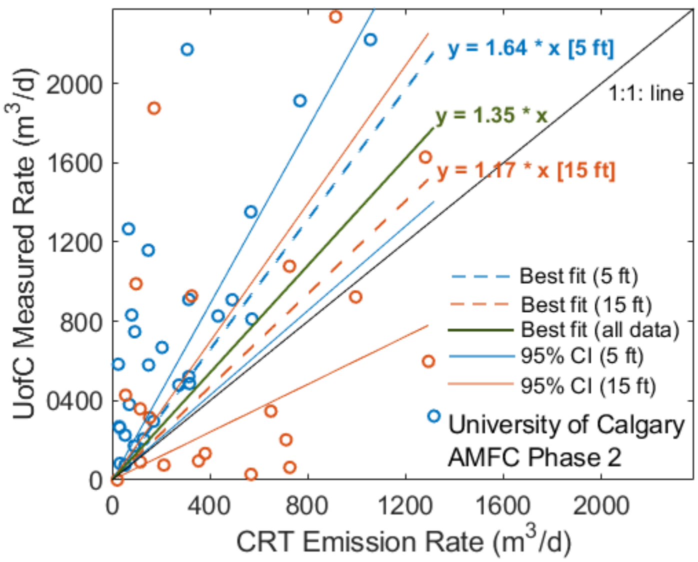


Figure 33: Parity chart of controlled releases conducted at the CRT site for the University of Calgary in AMFC phase 2.

Figure 34 shows the site-level emissions size distribution of UofC and QOGI at overlapping sites (n = 44). The size distributions are similar, with the top 10% of sites that both teams measured contributing to approximately 37% of total emissions.

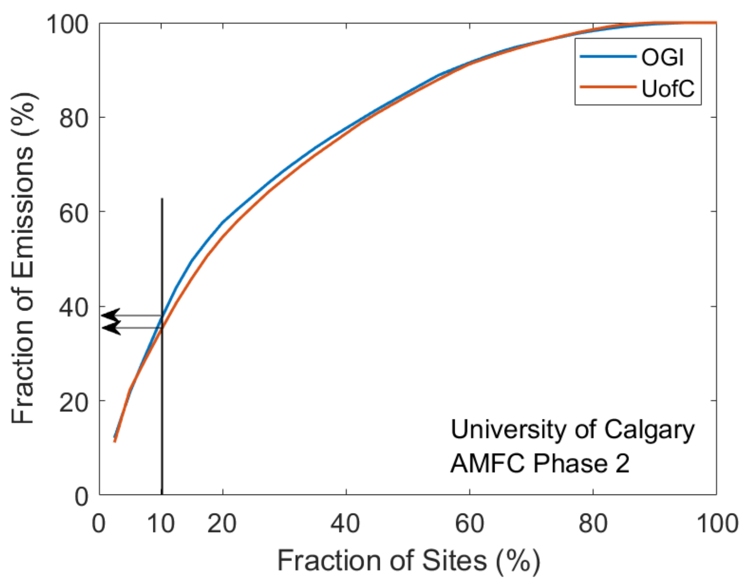


Figure 34: Normalized site-level emissions-size distribution of the University of Calgary and QOGI in AMFC phase 2.

Figure 35 shows the site-level quantification parity chart between QOGI and UofC at 44 overlapping sites. The slope of the regression line is 1.5, indicating an average over-estimation of approximately 50%.

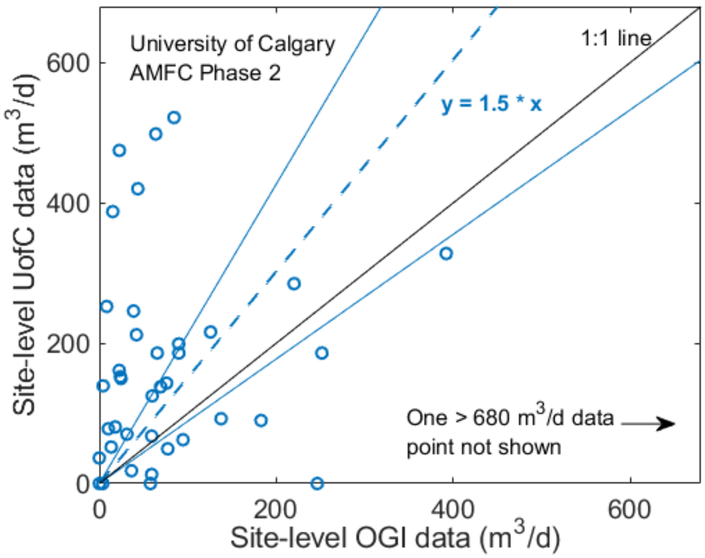


Figure 35: Site-level emissions quantification parity chart and regression coefficients between the University of Calgary and QOGI in AMFC phase 2.

Figure 36 shows the site-level quantification estimates of UofC in comparison with that of QOGI in both AMFC phase 1 and phase 2 campaigns for comparison. While the average quantification estimates of UofC and QOGI are very similar in the phase 1 campaign (290 m^3/d for UofC vs. 284 m^3/d for QOGI), UofC estimated a 33% higher average emission rate compared to QOGI in phase 2 (196 m^3/d for UofC vs. 147 m^3/d for QOGI).

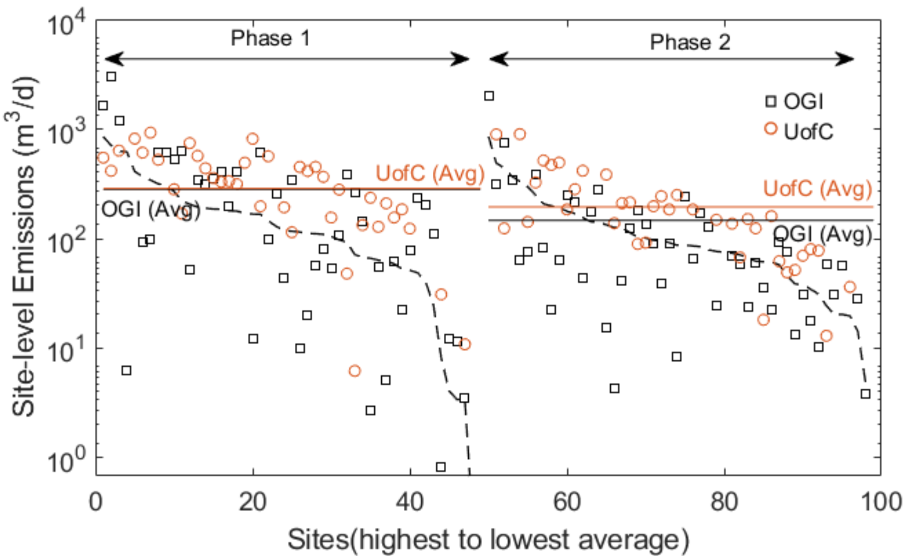


Figure 36: Site-level emissions estimate of QOGI (black squares) and UofC (orange circles) in AMFC phase 1 (left) and phase 2 (right) campaigns, ranked in descending order of average site-level emissions of all technologies (black dashed line). Both phase 1 and phase 2 here are shown for comparison. The average quantification estimates in each of the AMFC campaigns for QOGI (solid black line) and UofC (solid orange line) are also shown. In phase 1, the average quantification estimates from QOGI (284 m^3/d) nearly overlaps with that of UofC (290 m^3/d).

6.3. Sander Geophysics

Sander Geophysics tested an aerial mounted (fixed wing, light aircraft) off-axis integrated cavity output spectroscopy (OA-ICOS) sensor to detect atmospheric methane concentrations. The air is sampled through an inlet port mounted externally on the survey aircraft and is pumped through a particle separator filter prior to analysis by the OA-ICOS spectrometer. While the instrument measures atmospheric methane enhancements, gaussian inversion algorithms Markov-chain Monte-Carlo simulations are used to calculate ground location and emission rates of sources. In addition to methane, the aircraft is fitted with instruments that measure wind velocity, turbulence intensity, temperature, pressure, radar altitude, and GPS coordinates. The aerial surveys are typically conducted at 500 ft above ground depending on local regulations and atmospheric conditions. However, in the AMFC, the flight altitude was approximately 300 ft above ground. Sander flew for 7 of the 11 days of the program. Sander quantified site-level emissions wherever possible.

Table 15 summarizes Sander's performance in AMFC phase 2. The Sander team visited 39 sites, of which 32 overlapped with OGI. At an average survey speed of 6 sites per day, the Sander team took about 23 minutes per site to measure and quantify emissions. The Sander team performed multiple passes over each site, and the average measurement time reflects the time required for the plane to turn and pass over the site. Of the 32 sites that overlapped with OGI, Sander identified 28 sites with emissions also detected by OGI, and 4 non-emitting sites that was also found non-emitting by the QOGI team, for an overall site-level detection effectiveness of 100%. However, although Sander detected emissions at 28 sites where QOGI also detected emissions, emissions were only quantified at 4 sites due to unstable wind conditions.

Table 15: Summary of Sander Geophysics' performance in AMFC phase 2

Sander Geophysics – AMFC phase 2		**Metric**
Total number of sites visited		39
Average speed		6 sites/day
Average measurement time		23 minutes/site
Number of sites overlapping with OGI		32
Detection at overlapping sites	OGI > 0, Sander > 0	28
	OGI = 0, Sander = 0	4
	OGI = 0, Sander > 0	0
	OGI > 0, Sander = 0	0
Site level	Agreement with OGI	100% (32/32)
	Different from OGI	0% (0/32)

During the CRT tests, while the Sander team was able to detect the controlled releases correctly during each survey, they were unable to quantify most of the controlled releases due to unstable wind conditions. Sander surveyed 23 individual controlled releases, of which only 2 were quantified (see Table 17). The measurement distance (both vertical and horizontal) ranged from a minimum of 100 m to a maximum of 2600 m. Further improvements to the quantification algorithms employed by Sander could help address this challenge.

Table 16: Summary of controlled release results for Sander in AMFC phase 2

CRT releases	**True Release Rate (scfh or m^3/d)**	**Sander Estimate (scfh or** m^3/d**)**
1	226 scfh or 154 m^3/d	90 scfh or 61 m^3/d
2	451scfh or 307 m^3/d	418 scfh or 284 m^3/d

3 – 23	Various	Unable to quantify

As mentioned above, the Sander team was only able to quantify emissions at 4 sites where they overlapped with QOGI. As a result, it is not possible to derive a statistical inference from the site-level emissions distribution. The results of the quantification and its comparison to QOGI are shown in Table 17. On average, based on this limited number of results, Sander overestimates site-level emissions by about 2.5 times, compared to QOGI. Assessing whether this result is due to systematic overestimation or outliers owing to unstable atmospheric conditions will require further detailed controlled release testing, and a larger data set that allows for statistical analysis.

Table 17: Comparison of site-level emissions quantification between Sander and OGI in AMFC phase 2

Site Number	**Sander Quantification (scfh or** m^3/d**)**	**OGI Quantification (scfh or** m^3/d**)**
24	728 scfh or 495 m^3/d	460 scfh or 313 m^3/d
31	1114 scfh or 757 m^3/d	506 scfh or 344 m^3/d
34	1370 scfh or 931 m^3/d	112 scfh or 76 m^3/d
52	793 scfh or 539 m^3/d	525 scfh or 357 m^3/d
Average	**1001** scfh or 680 m^3/d	**401** scfh or 273 m^3/d

Figure 37 shows the individual site-level emissions estimate comparison between QOGI and Sander Geophysics in AMFC phase 2, ranked in descending order of the average site-level emissions from all technologies.

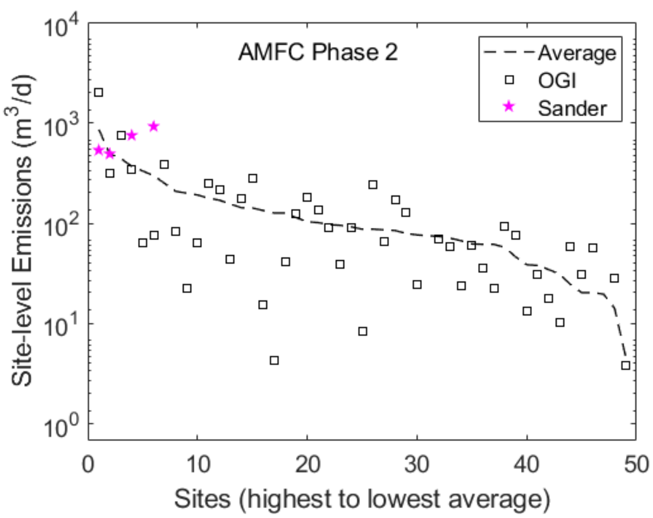


Figure 37: Site-level emissions estimate of QOGI (black squares) and Sander Geophysics (pink stars) in AMFC phase 2 campaign, ranked in descending order of average site-level emissions of all technologies (black dashed line).

6.4. FLIR Technologies

FLIR Technologies (FLIR) tested a handheld, uncooled infrared (IR) camera (FLIR GF77) to detect component-level emissions in AMFC phase 2. At this time, the uncooled camera is designed for emissions detection, not quantification, for both site surveys and CRT measurements. FLIR tested this method for 5 days of the 11-day field program between November 14 – 18, 2019.

In this section, FLIR refers to the FLIR Technologies team using the uncooled infrared camera (FLIR GF77) while OGI refers to the ground team conducting baseline survey using the cooled infrared camera (FLIR GF320).

Table 18 summarizes FLIR's uncooled camera performance in AMFC phase 2. Over the course of 5 days, FLIR conducted 26 site surveys, of which 24 overlapped with QOGI. On average, FLIR spent about 36 minutes on each site, detecting methane emissions at the component-level. This average measurement time is comparable to that of typical OGI surveys of small sites (well-pads with 1 or 2 wells) without the need for any quantification. Of the 24 overlapping sites, FLIR identified 5 sites with emissions also detected by OGI, and 2 non-emitting sites that was also found non-emitting by the OGI team, for an overall site-level detection effectiveness of 29%. At 17 sites, FLIR did not detect emissions when OGI detected emissions. The large difference between OGI and FLIR (71%) can be explained by the detection thresholds of the respective cameras. Uncooled infrared cameras have lower sensitivity and require a higher noise-limited temperature difference than cooled infrared cameras such as the one used by OGI (FLIR GF-320). Therefore, it is likely that the uncooled IR camera could not detect small emissions that were detected by the OGI crew. For example, NETD specification – a proxy for detection threshold – for the cooled and uncooled infrared cameras are 25 millikelvin (mK) and 15 mK, respectively.

Table 18: Summary of FLIR Technologies' performance in AMFC phase 2

FLIR Technologies – AMFC phase 2		**Metric**
Total number of sites visited		26
Average speed		5 sites/day
Average measurement time		36 minutes/site
Number of sites overlapping with OGI		24
Detection at overlapping sites	OGI > 0, FLIR > 0	5
	OGI = 0, FLIR = 0	2
	OGI = 0, FLIR > 0	0
	OGI > 0, FLIR = 0	17
Site level	Agreement with OGI	29% (7/24)
	Different from OGI	71% (17/24)

FLIR also measures emissions at the component-level. At the 5 sites where the FLIR team detected emissions, they recorded the emitting source of equipment as summarized in Table 19. The FLIR team only reported emissions from buildings and wellheads at all the 5 sites, resulting in a relatively low detection effectiveness of 26% and 14%, respectively, compared to OGI. Because FLIR did not quantify emissions, it is not possible to compare the emission-size distribution and quantification against OGI.

Table 19: Equipment-level comparison of emissions detection between FLIR and OGI in AMFC phase 2 across six major equipment categories.

Equipment type	**FLIR Detect**	**OGI Detect**	**Effectiveness (%)**
Building	5	19	26%
Compressor	0	0	-
Wellhead	1	7	14%
Tank	0	0	-
Flare	0	0	-
Separator/Dehydrator	0	0	-

6.5. Tecvalco

Tecvalco used a hybrid system for methane emissions measurements in the AMFC phase-2 program. Emissions were detected using a handheld, methane-selective sensor (Gas-Track LZ30) based on tunable diode laser spectroscopy (TDLAS), with a typical concentration-path length measurement output. After detecting an emission, the Tecvalco team used a digitized positive displacement diaphragm meter (Hawk Vent Gas Meter) to measure emission flow rate. Depending upon safety and access considerations, this flow meter was directly attached to the emitting source to measure gas flow rates. Tecvalco tested this method for 5 days of the 11-day program from November 19 to 23, 2019. Following the field program in November, it has not been possible for the study team to receive completed data sets representing Tecvalco's participation. The results presented here correspond to data that have been submitted through February 22, 2020; more results will be added as supplementary material or addenda if additional data are made available.

Table 20 summarizes Tecvalco's performance. Over the course of 5 days, Tecvalco conducted 14 site surveys (according to submitted daily field logs); however, the science team is only in receipt of quantified data for 10 site surveys, 9 of which overlapped with OGI. Of these 9 surveys, Tecvalco and OGI both detected emissions at 8 sites for an overall detection effectiveness of 89%. At the one remaining site, Tecvalco did not detect emissions while the OGI team detected emissions. On average, Tecvalco measured at the rate of 3 sites per day, with the team taking approximately 52 minutes per site to detect and quantify emissions. The higher average measurement time compared to other handheld teams account for the quantification step performed by Tecvalco that included a separate equipment (Hawk Vent Gas Meter) to measure direct flow rates from the emitting source.

Table 20: Summary of Tecvalco's performance in AMFC phase 2

Tecvalco		**Metric**
Total number of sites visited		14 (10)
Average speed		3 sites/day
Average measurement time		52 minutes/site
Number of sites overlapping with OGI		9
Detection at overlapping sites	OGI > 0, Tecvalco > 0	8
	OGI = 0, Tecvalco = 0	0
	OGI = 0, Tecvalco > 0	0
	OGI > 0, Tecvalco = 0	1
Site level	Agreement with OGI	89% (8/9)
	Different from OGI	11% (1/9)

Tecvalco also measured emissions at the component-level that have been aggregated at the equipment-level for comparison as summarized in Table 21. At the 5 sites where data were reported, Tecvalco's effectiveness ranged from 30% in buildings to 50% at wellheads and separators. However, emissions were quantified only if they were point sources that was also accessible and did not pose any safety challenge.

Table 21: Equipment-level comparison of emissions detection between Tecvalco and OGI in AMFC phase 2 across six major equipment categories.

Equipment type	**Tecvalco Detect**	**OGI Detect**	**Effectiveness (%)**
Building	3	10	30%

Compressor	0	0	-
Wellhead	2	2	50%
Tank	2	5	40%
Flare	0	0	-
Separator/Dehydrator	3	6	50%

Figure 38 shows the controlled release test data for Tecvalco. At the time of reporting, the science team was in possession of data from 10 releases. All CRT releases for Tecvalco were conducted at 5 feet, because of the need to attach a flowmeter directly to the emitting source. Tecvalco achieved high accuracy in quantification with a linear regression slope of 1.04. This result was expected, because flow-meters measure flow directly and the process of quantification (more accurately, measurement, in this scenario) does not involve inferences from proxy data such as concentration or imaging. The need to physically attach the flowmeter to take measurements limits this method to a narrow range of emitting sources.

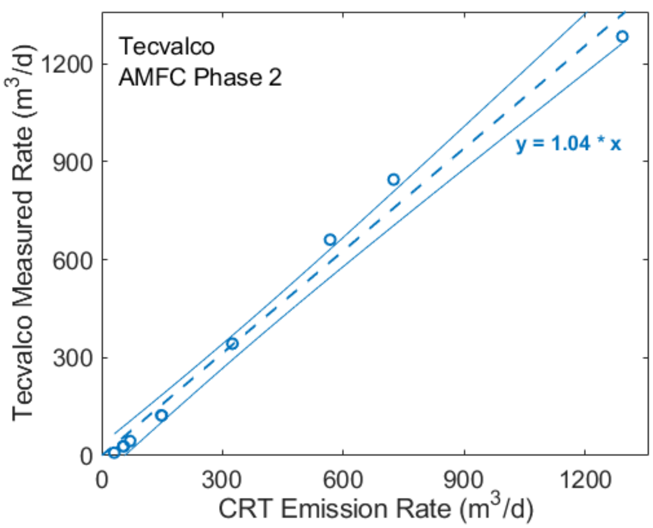


Figure 38: Parity chart of controlled releases conducted at the CRT site of Tecvalco in AMFC phase 2

Of the 10 overlapping sites, Tecvalco quantified emissions at four sites from emission sources that were accessible and safe to measure. Therefore, site-level quantification comparisons between QOGI and Tecvalco does not represent an exhaustive accounting of all emissions sources detected by Tecvalco at the site. Because there were only 4 sites with limited quantification data statistical analysis was not possible, and we present the results in Table 22 We note that Tecvalco's site-level quantification may not include all emissions detected by the Tecvalco at any given site.

Table 22: Comparison of Tecvalco's site-level quantification with that of QOGI in AMFC phase 2 (note: Tecvalco's site-level quantification does not include all emissions at a given site – only emissions that were accessible and safe to use the gas flow meter were quantified)

Site Number	**Tecvalco Quantification (scfh** or m^3/d**)**	**OGI Quantification (scfh** or m^3/d**)**
24	709 scfh or 482 m^3/d	460 scfh or 313 m^3/d
25	Unable to quantify	46 scfh or 31 m^3/d
30	6 scfh or 4 m^3/d	189 scfh or 128 m^3/d
38	10 scfh or 7 m^3/d	42 scfh or 29 m^3/d
44	49 scfh or 33 m^3/d	262 scfh or 178 m^3/d

7. Study Limitations

The Alberta Methane Field Challenge (AMFC) is the first large-scale field testing of alternative methane leak detection technologies at producing oil and gas facilities in Canada. The field tests provided vital data on the detection, localization, and quantification performance of a range of technologies including fixed sensors, handheld sensors, drone-, truck-, and plane-based systems. Through the course of both the phases of the program, we learned several important features and limitations of the study. These are summarized here for readers of this report and so future studies and field deployment protocols can consider these suggestions.

1. **The average survey speed measured in this study should not be assumed to be a proxy for expected survey speed as part of an LDAR program field deployment.** The teams collected data from sites that would be useful for analysis and comparison with OGI that might not be required as part of a typical LDAR survey. Because multiple teams were deployed simultaneously, there were delays when an incoming team at a site was waiting for another team on the site to finish measurement, or to coordinate site visit order based on the positions of other teams instead of an optimized survey route. As with the survey speed interpretation for any team, the experimental conditions of the program inherently reduce efficiency (encountering other teams on-site, adjusting daily workflow to avoid other teams, etc.). In practice, one can expect survey speeds to be higher than what was demonstrated as part of this study.
2. **Attribution of the differences in emissions detection between baseline QOGI survey and an alternative technology is a challenging problem.** For example, many technologies measured zero emissions at sites where the QOGI teams found emissions. This can be due to several reasons: one, technologies incorrectly reported zero emissions at a site with emissions; two, intra-day variation in emissions at the site could have resulted in technologies being unable to witness intermittent emissions seen by OGI; three, differences in detection thresholds between the technology and the OGI system; and four, weather-related challenges in identifying emissions when the technology was on-site.
3. **Effective detection of emissions at height is dependent on the sampling strategy.** Technologies that measure atmospheric methane concentrations closer to the ground (e.g., truck-based systems) could potentially exhibit lower detection effectiveness at tanks and flares compared to other technologies because of the height of the emission source. Flare stacks and tanks are significantly higher than other equipment on site and under suitable atmospheric conditions, it is possible for a methane plume to not intersect with the air sampling location of the technology, resulting in a missed detection [34].
4. **Diffuse emission sources are harder to detect than point sources.** Diffuse emission sources are harder to detect, partly resulting in the low effectiveness observed across many technologies. The diffuse nature of emissions from buildings would materialize on a laser-based sensor as a generalized methane concentration enhancement without pointing to a specific localized source. In other words, diffuse emissions disperse into the background, thereby significantly reducing concentration enhancements above the atmospheric background.
5. **Repeated measurements at a producing oil and gas site can show significant variation in emissions.** Several reasons can be postulated. First, emissions can exhibit variations on the scale of hours and days, based on operations at any given site. Second, site-level emissions measurements can be affected by changes in local weather, atmospheric conditions, and the physical set-up of the site. Therefore, repeat measurements using high-speed methods can be used to further improve confidence

in the emissions quantification and potentially identify any intermittent processes on site. Future studies to understand the temporal behavior of methane emissions would be useful.

6. **Quantification accuracy is a function of several variables such as algorithmic effectiveness, temporal variation in emissions, or weather that make attribution challenging.** Differences in quantification between alternative technologies and QOGI can result from several factors. These can be weather-related (wind speed, wind direction, turbulence,), survey characteristics (survey speed, air sampling location), emissions characteristics (gas composition, diffuse vs. point source), or algorithmic challenges in converting raw measurements to emission rates. Detailed controlled release test measurements should be conducted to shed light on quantification effectiveness.

In short, differences in detection, localization and quantification between technologies can be attributed in part to environmental, operational and other challenges and in part to the performance of the underlying technology. Selection of an appropriate method of deployment and each method's role in a Fugitive Emission Management Program should consider and attempt to mitigate these challenges in order to maximize its effectiveness.

8. Conclusions

The Alberta Methane Field Challenge (AMFC) program sought to evaluate the performance of alternative methane leak detection technologies to detect and quantify methane emissions at producing oil and gas facilities. The AMFC program was scheduled in two phases – one in June 2019 and the other in November 2019. The program details were similar across the two phases except for the addition of a controlled release test site in phase 2. Overall, 12 fixed, truck-, drone-, and plane-based technologies were tested as part of AMFC – 7 in phase 1 and 5 in phase 2. The following are the broad conclusions from this study.

First, quantitative optical gas imaging (QOGI) technology is effective in providing comprehensive estimates of all methane emissions at oil and gas facilities. The aggregate error (18%) from the controlled release tests is comparable to that of the Hi-Flow sampler (~10%). In addition, the QOGI provides emissions for a large range of emissions – from about 10 scfh (7 m^3/d) to over 3000 scfh (2038 m^3/d), significantly higher than the conventional Hi-Flow sampler's limit of 480 scfh (326 m^3/d). Monte Carlo analysis of these results can help us understand the importance of sample-size in interpreting QOGI data (see full report for detailed analysis). We note that errors in individual emissions measurements will be higher than aggregate estimates. Thus, it is critical for stakeholders to **not** interpret estimates of QOGI-based emissions data individually.

Second, most technologies evaluated in the AMFC are effective at detecting atmospheric methane emissions concentrations and demonstrate wide performance variation a variety of capabilities across survey speed, localization, and quantification that must be carefully matched with applications. Overall, aerial and truck-based systems have distinct advantages in survey speed over other ground-based technologies. However, they will all require secondary inspection to find and potentially repair the emitting component. Thus, the ability of *'fast technologies'* to perform as effective screening systems to identify high-emitting sites rests on their quantification effectiveness. Without reasonably effective quantification, these systems risk identifying sites with any methane emission above the detection threshold for potential follow-up. Drone based systems can be effective in detecting and quantifying methane emissions in situations that pose access challenges. The combination of three degrees of freedom i.e., pitch, yaw and roll and the ability to measure close to the emission source makes drones effective at quantifying sources such as flares or tanks more easily than conventional Hi-Flow based approaches.

However, there are not significant advantages on survey speed compared to OGI-based LDAR surveys. Finally, while fixed sensors tested in the AMFC program provided continuous measurements of methane concentrations, significant improvements in data analytics are required before they can be effective as methane detection solutions where a follow-up and repair would be possible.

Third, accurate quantification remains challenging – some technologies can provide good order of magnitude estimates of site-level emissions compared to QOGI. Drone-based and aerial teams were the most effective at correctly estimating the order of magnitude estimate of methane emissions as seen in Figure 39, which show the parity chart of quantification rank between the technologies and OGI. For these technologies, sites that showed the highest emissions in the OGI survey in AMFC, on average, also exhibited high emissions in the OGI survey, even if the absolute emissions estimate were different. This implies that technologies are effective at classifying relative emissions sizes and could be an effective screening tool.

The differences in quantification estimates between participating teams and QOGI can have multiple potential causes that are method-dependent, emission-dependent, or weather-dependent. Method-dependent causes include the effectiveness of algorithms in converting raw concentration data to emission rate information, survey speed, and sampling procedures. Emission-dependent causes include intermittency and the nature of emissions (diffuse vs. point source, high pressure vs. low pressure, etc.). Weather-dependent causes include the height of atmospheric boundary layer, local turbulence, the presence of smoke or snow, wind speed, and wind direction. The impact of these different parameters on technology performance can vary depending on the survey procedure – stakeholders would find it useful to analyze the results presented here to match methods with appropriate applications.

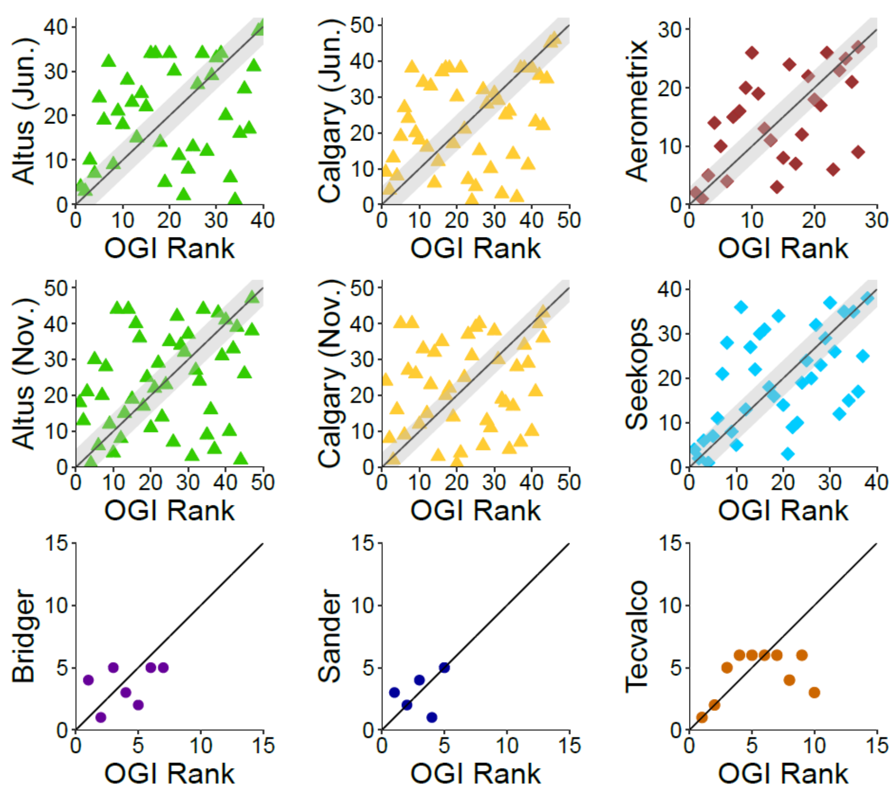


Figure 39. Parity chart of quantification rank at the site-level (sites arranged in descending order of emission rate with site 1 corresponding to the site with the largest emissions). The shaded region shows a 10% error

threshold for site rank. The 10% error threshold is not marked for Bridger Photonics, Sanders, and Tecvalco because of small sample sizes.

Fourth, in-field controlled releases are effective in calibrating the quantification capabilities of new technologies that account for local weather conditions. The performance of technologies in controlled release tests is affected by weather conditions to varying degrees. Optical gas imaging cameras have reduced sensitivities in high wind conditions or cloudy days. Truck-based systems may have difficulty in detecting emissions at height (tanks or flares) depending on wind and atmospheric boundary layer conditions. Similarly, drones may find it challenging to map flow rates from concentration profiles on low-wind days without significant plume dispersion. In-field controlled release tests are cost-effective, convenient, and greatly improve the confidence in emissions data provided by new technologies. Furthermore, because these tests occur contemporaneously as the actual oil and gas site survey, the impact of wind, weather, and other atmospheric conditions are factored into the controlled releases. Therefore, these in-field tests provide an ideal platform to calibrate technology performance in real-time. Future work with new technologies, whether as part of a research study or an LDAR survey, should strongly consider employing such in-field controlled releases to improve the quality of the data collected.

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