Multi-scale Methane Measurements at Oil and Gas Facilities Reveal Necessary Framework for Improved Emissions Accounting

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Abstract

Methane mitigation from the oil and gas (O&G) sector represents a key near-term global climate action opportunity. The effectiveness of mitigation strategies rests on the ability to quantify spatially and temporally varying methane emissions more accurately than existing approaches. Advances in technologies have enabled improvements in methane emissions measurements and monitoring, In this work, we demonstrate a quantification, monitoring, reporting, and verification framework that pairs snapshot measurements with continuous emissions monitoring systems (CEMS) to reconcile measurements with inventory estimates and account for intermittent emissions events. We find site-level emissions exhibit significant intra-day and daily emissions variation. Snapshot measurements of methane can span over three orders of magnitude and may have limited application in developing annualized inventory estimates. Consequently, while official inventories underestimate methane emissions on average, emissions at individual facilities can be lower than inventory estimates. Using CEMS, we characterize distributions of frequency and duration of intermittent emission events. Technologies that allow high sampling frequency such as CEMS, paired with a mechanistic understanding of facility-level events is key to accurate accounting of short-duration, episodic, and high-volume events that are often missed in snapshot surveys, and to scale snapshot measurements to annualized emissions estimates.

1. Introduction

Reducing methane emissions from the oil and gas (O&G) supply chain is a key component of near-term climate action [1]. Over 100 countries have pledged to reduce methane emissions 30% by 2030 as part of the United Nations 2021 Conference of Parties [2]. Innovation in technologies to quantify methane emissions can now enable target-based approaches to emissions mitigation and differentiation across operators. The potential for these new mitigation approaches has led companies, investors, consumers, and governments to focus on finding ways to accurately monitor, measure, and mitigate methane emissions [3]–[5]. Characterizing the GHG intensity of individual supply chains through a life cycle approach is critical for informing differentiated gas supplies and policy frameworks that depend on accurate emissions estimation [6]. The success of these new approaches, therefore, rests on our ability to accurately measure methane emissions that accounts for spatial and temporal variations and the skewed nature of emission distributions [7].

Recent advances in methane measurement technology have improved our understanding of methane emissions [8]–[12]. Large-scale aerial surveys in the Permian basin demonstrate the importance of identifying intermittent super-emitters [13], [14]. Cusworth et al. showed that the average persistence of large emissions is only about 26%, suggesting the need for continuous measurements to detect and mitigate such events [14]. A detailed study of temporal variations in methane emissions suggests potential impact of measurement time on emissions estimates where one-time events like liquids unloadings preferentially occur during certain periods of the work-day [15]–[18]. The effectiveness of and trust in approaches to address methane emissions, therefore, depends on the availability of accurate methane emissions estimates that vary in frequency, duration, and across geographic locations.

Empirical measurements of methane have also highlighted the limits of conventional inventory development using activity and emissions factors [19]. Analysis of recent field measurements across O&G production facilities in the US and Canada show that, on average, measured emissions are approximately 60% higher than official inventory estimates [20], [21]. This is because engineering-based methods rely on component-level activity and emissions factors that are often outdated or poorly characterized [22]. A decomposition study of this discrepancy between measurements and inventory pointed to an underestimation of emission factors associated with tanks and equipment leaks [19]. Most bottom-up, component-level studies of methane emissions show highly skewed distributions – from sites that do not have any detectable emission to sites with emissions orders of magnitude larger than the sample average [7], [23]–[25]. Furthermore, intra-day variations in emissions from specific equipment like tanks have also been observed [16]. Thus, except in simple site configurations, low frequency or snapshot measurements tend to have high variability and are unsuitable for asset-level differentiation. Advances in technologies such as continuous emissions monitoring systems (CEMS) could provide the high-resolution data needed to characterize temporal variability in methane emissions [26]–[28]. Recent research has also shown a systematic variation in emissions over time as wells get older and the composition of oil, gas, and liquids change [29], [30]. Compared to a conventional inventory, snapshot measurements may result in either under- or overestimation of site-level emissions. To develop a more accurate annualized emissions inventory estimate, measurements require high temporal resolution to detect and quantify intermittent emission events [29], [31].

Many jurisdictions have used leak detection and repair (LDAR) programs to mitigate methane emissions from O&G operations [32]–[34]. Recent randomized controlled experiments suggest that these programs are effective in reducing fugitive methane emissions [35], [36]. However, several recent studies note that the majority of methane emissions come from large equipment (e.g., storage tanks), malfunctioning or episodic sources that are not typically considered leaks [19], [37], [38]. These abnormal emissions have limited or no "monitoring" benefits from typical LDAR programs nor can they reliably be independently verified solely by top-down aerial or drone monitoring methods due to low sampling frequency. Thus, no currently existing technology is sufficient on its own for capturing the temporal fluctuations of methane emissions, which is necessary to develop accurate annual emissions estimates.

To address gaps in typical LDAR programs, new frameworks such as "responsible natural gas" or "certified natural gas" have emerged as a mechanism to assure customers of low methane leakage across the supply chain. However, no empirical measurement protocol has yet been demonstrated that can provide reasonably accurate supply chain specific methane emission estimates necessary to assess such claims. The U.S. federal government has created an inter-agency task force to identify and deploy tools to measure, monitor, report, and verify GHG emissions [3]. Yet, currently available frameworks do not provide the level of transparency and rigor to be able to build trust among the public through independent, third-party verification.

In this work, using multi-scale measurements of methane emissions across three U.S. natural gas basins, we demonstrate the role of high spatial and temporal resolution data in advancing target-based approaches to emissions mitigation. Through this multi-basin field study, we describe how a measurement framework that accounts for spatial and temporal variations in methane emissions can help develop accurate emissions inventory estimates. Importantly, this study could serve as a guideline for a universal framework for measurement-based protocols. Stakeholders in the O&G industry, government, and financial organizations can adapt this framework for more representative emissions estimation across the supply chain.

2. Methods

The multi-scale measurement approach is embedded within a quantification, monitoring, reporting, and verification (QMRV) protocol. This protocol combines different elements of a measurement-based framework that together provides accurate inventory estimates. These elements include emissions quantification through multi-scale measurements, analysis and monitoring of intermittent emission activity, detailed reports on site operations and measurement schedule, and an independent verification process. Details of the QMRV protocol are provided in the SI (see SI section S1). Here, we describe the measurement framework and results that are central to the QMRV protocol. The measurements were conducted in two phases – a baseline phase to estimate emissions at all sites prior to the study beginning and an enhanced monitoring phase that involved collection of high spatial and temporal resolution data at each site.

2.1. **Design**

A total of 38 facilities from five natural gas producers participated in the study, referred to as the QMRV project, across the Marcellus, Haynesville, and Permian basins, accounting for over 0.4 billion cubic feet per day (bcfd) in the aggregate. The QMRV project consisted of three phases: baseline emissions measurements with multi-scale methods, enhanced monitoring using CEMS for a period of 6 months, and an end-of-project aerial snapshot measurement (SI section S1). We deployed four snapshot emission measurement technologies concurrently at these enrolled facilities as part of the QMRV project, including satellite measurements during the baseline phase, and two CEMS technologies for continuous monitoring during the enhanced monitoring phase as part of the QMRV project [4].

The snapshot measurements include an optical gas imaging (OGI) camera paired with a Hi-Flow sampler, aerial mass balance technology using a drone and a meteorological station conducted by SeekOps, Inc. ("SeekOps"), a LiDAR plume identification system using an aircraft conducted by Bridger Photonics ("Bridger"). All three technologies have undergone controlled tests and field trials in the past with the performance data made public through peer-reviewed studies [8], [39]–[41]. In addition, satellite measurements were conducted concurrently at the enrolled assets when weather conditions allowed. The OGI technology and SeekOps require site access to measure emissions, whereas Bridger does not require site access or operator presence to conduct their measurements. Because of the speed of aerial surveys, Bridger was tasked with observing emissions from non-enrolled assets operated by the producers participating in the QMRV project, to assess if emissions at sites selected for monitoring are representative of the producers' local assets. OGI with Hi-Flow measures emissions at the component-level, similar to conventional LDAR programs and can distinguish between leak and vent emissions. Facility-level emissions are calculated by aggregating individual equipment-level emissions. SeekOps and Bridger detect and quantify emissions at the equipment-level and typically do not distinguish between leaks and vents. Facility level emissions are estimated by aggregating individual equipment-level emissions. In this paper, we have anonymized the basin names and present results from the baseline phase and key observations from the enhanced monitoring phase of the project.

2.2. **Field measurements**

The OGI, SeekOps, and Bridger teams collected data from 8 facilities in Basin A from June 20-24, 2021, from 5 facilities in Basin B from July 26-28 and August 3, 2021, and from 25 facilities in Basin C from August 23-26, 2021. Multiple surveys were conducted by each measurement technology, depending on survey speed and time, and were designed to be contemporaneous to ensure comparability of the measured data. Seek Ops, which typically takes 1 – 3 hours per facility, completed up to 2 surveys of each site. Bridger Photonics, being an aerial technology, measured each site 6 – 11 times across all basins. Several recent peer-reviewed studies describe the performance parameters of these technologies in detail [8], [41]. Emissions attribution was done by direct data collection from technologies and cross-referencing with operator insight and field photos. The OGI+Hi-Flow team recorded the equipment associated with emitting components in their survey reports. The SeekOps team reported emissions by equipment group in basins A and B. In basin C, SeekOps was unable to measure at the equipment-level due to safety concerns and therefore only provided site-level emissions data. The Bridger team reported emissions by location on site without source identification to specific equipment. To attribute emissions, we compared the field photos from Bridger against those from SeekOps and Google Earth and manually labeled the equipment for each emission sources. Satellite-based observations were conducted at the 38 facilities. However, the instrumentation's sensitivity to cloud cover and aerosols in the atmosphere and surface features like water bodies resulted in few successful measurements. A satellite measurement is successful when conditions allow for data acquisition, regardless of whether an emission is identified. During the baseline phase, satellite data collected on days with favorable environmental and atmospheric conditions did not see any emissions from any of the enrolled facilities, likely because of the high detection thresholds for satellite-based emissions detection.

CEMS were installed at facilities in basin A and basin B for a 6-month period to assess temporal variations in methane emissions and estimate the frequency and duration of intermittent emission events. Two separate solutions were installed – Sensor A (laser absorption spectroscopy) and Sensor B (metal-oxide sensor). The number of sensors at each site varied from about 3 to 6 based on the size of the site, number of equipment with potential to emit methane, and prevailing wind direction and local geography.

2.3. **Inventory estimation**

Site-level measurements from SeekOps and Bridger are used to develop measurement-informed inventory (MII) estimations. MII refers to a composite emission estimate for a site based on measurements from all technologies that surveyed the site. Measurements from OGI are not included in these estimates because OGI does not capture all emission sources at a facility such as engine slip and hence underestimates site-level emissions (see SI section S2). SeekOps provided a summary report of measured emissions and wind-roses with detailed notes at each site. Measurements from all equipment on each facility were aggregated to calculate the full facility-level emission rate. A high-resolution field photo was also provided for each facility. Bridger typically performed 2 to 3 rounds of measurements per day for every site and provided a detailed breakdown of emissions measured from each flyover by emissions location. Bridger conducted multiple rounds of measurements throughout the day as well as multiple passes over the same facility within a few minutes during each round of measurement. We first calculate the average emission rate from an equipment in each round by averaging across multiple passes. Emissions across all equipment were aggregated for each round to estimate site-level emissions. Finally, emissions across multiple rounds on the same day were averaged to estimate a daily average emission rate for each facility.

In addition to measurements, each operator was also required to submit conventional emissions inventory reports, estimated through EPA’s GHG Reporting Program (GHGRP) methods for individual sources [42]. Emissions that are known to be excluded in the GHGRP were also provided as supplementary information to allow comparison of measured emissions with inventory estimates (see SI section S3).

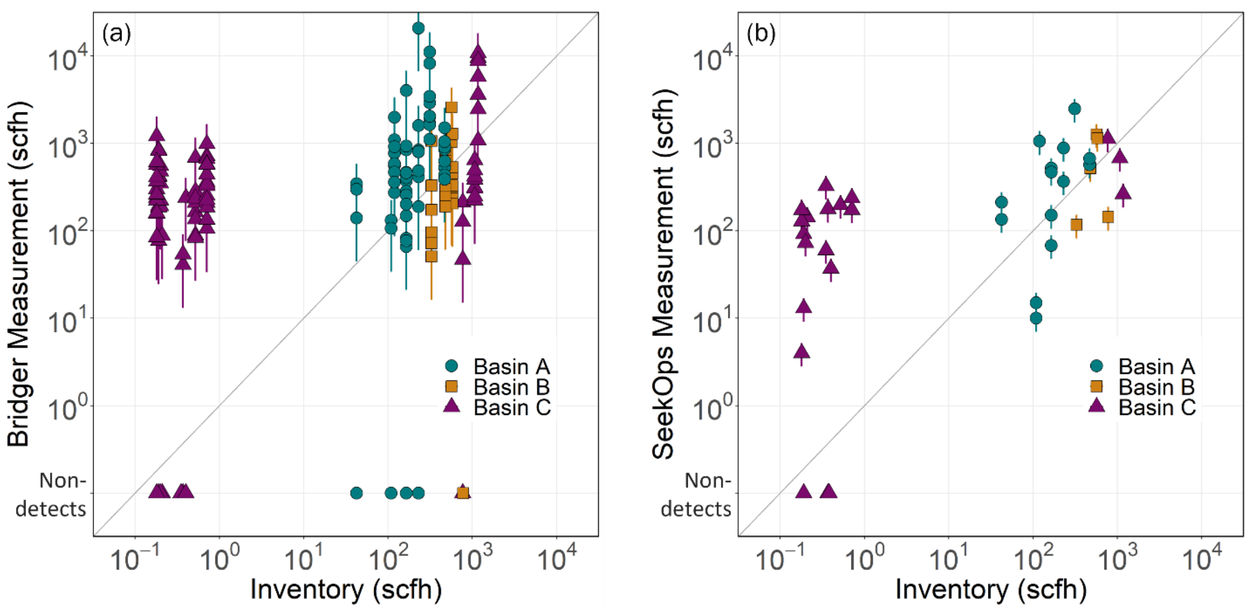
3. Results

Each measurement by a technology is assumed to be an independent and true (within measurement uncertainty and technology limitations) snapshot estimate of methane emissions. Thus, multiple measurements at a single facility are treated as independent and equally valid data points and are averaged with equal weight to all other measurements. Because measurements by both SeekOps and Bridger were contemporaneous, potential diurnal variations in emissions is not expected to bias this approach.

3.1. Inventory estimates vs. measurements

Methane emissions vary significantly in time and individual or a few snapshot measurements alone are insufficient to estimate an annualized emissions estimate. The significance of accounting for spatial and temporal variations in emissions through multiscale, contemporaneous measurements has been documented in the literature [16], [43]. Conventional engineering-based inventory development methods, such as the EPA GHGRP employ outdated emission factors and do not account for emissions variations across assets, especially from high-emitting or super-emitting events, resulting in significant underestimation compared to measurements [19]. Furthermore, if all operators are required to use identical national-level emissions factors when developing engineering-based inventory estimates, differentiation across operators is then strictly limited to differences in activity data without any consideration for design, operational, or maintenance practices. Thus, conventional engineering-based inventory estimates of emissions have limited application in target-based approaches to emissions reduction, such as supply-chain or asset-specific certification.

Figure 1 shows a parity chart of individual site-level methane emissions across three basins measured using the aerial (Bridger) and drone-based (SeekOps) survey platforms as well as the operator-estimated methane inventory calculated using GHGRP methodology. We make several critical observations. First, site-level methane emissions measured through snapshot surveys span over three orders of magnitude – from less than 50 standard cubic feet per hour (scfh) to over 10,000 scfh. This suggest that conventional inventory estimates are not representative of site-level emission on the time scale of hours to days. Second, average site-level emissions measured across each basin are higher than inventory estimates, a finding in line with recent published studies [20], [21]. For example, average site-level emissions, averaged across both measurement technologies, in basin A, basin B, and basin C are 1081 scfh, 473 scfh, and 374 scfh, respectively. By comparison, the average GHGRP-based inventory estimates in the three basins are 201 scfh, 546 scfh, and 151 scfh, respectively. In basin B, the GHGRP-based inventory estimate is higher than measurement average because of one site whose inventory estimate was based on 2020 values with an unusually large number of unloading operations not seen during measurements. Excluding this site, the average measurement informed inventory and GHGRP-based inventory estimate of all remaining sites are 586 scfh and 488 scfh, respectively. Third, significant variation in site-level emissions implies that measured individual snapshot emissions can be lower or higher than inventory estimates, depending on the time of measurement. In basin A, 2 of 8 sites have measured emissions lower than inventory estimates as measured by both Bridger and SeekOps. In basin B, all five sites have measured emissions by Bridger lower than inventory estimates. On the other hand, GHGRP-based estimates of emissions in 7 out of 25 sites in basin C are consistently at least one order of magnitude smaller than measured emissions. Thus, while it is true that aggregate measurement-based estimates of emissions are higher than inventory estimates, they are not sufficient for site-specific inventory development. This can be attributed to the use of static emissions factors in inventory estimates associated with time varying emission sources such as fugitives or tanks.



Measuring the frequency, duration, and volume of such time varying sources is critical to developing quasi real-time, site-specific emissions estimates. Fourth, site-level emissions exhibit significant intra-day variation. Repeat measurements of site-level measurements by Bridger show up to an order of magnitude variation in emissions – these are not restricted to specific site-types but generally observed across all three basins. For example, one site in Basin B exhibited emissions between 51 scfh and 1062 scfh, with an inventory estimate of 328 scfh.

Figure 1: Parity chart of individual, aggregate, site-level emissions (y-axis) as measured by Bridger Photonics (Figure 1a) and SeekOps (Figure 1b) in comparison with GHGRP-based inventory estimates

(x-axis) for each of the sites in basins A (turquoise circles), B (yellow squares), and C (purple triangles). All measurements were conducted in one week at each basin. Error bars indicate measurement uncertainty of Bridger and SeekOps technologies as determined through controlled release tests [9], [41].

3.2. Equipment-level temporal variation in emissions

Site-level temporal variation in emissions can be attributed, in part, to specific equipment groups. Figure 2 shows temporal variation in tank emissions from sites in basin A and B measured by both Bridger and SeekOps. Recent field studies of methane emissions have demonstrated that tanks are one of the largest sources of methane emissions from upstream O&G facilities [35], [37]. Measurements in both basin A and B show that distribution of individual emissions measurement from tanks span three orders of magnitude – from as low as 10 scfh to around 10,000 scfh. Averaging emissions from each site across all measurements, we calculate average tank emission rates of 597 scfh and 239 scfh in basin A and basin B, respectively. Thus, individual estimates of tanks emissions can be multiple standard deviations away from the time-averaged emissions estimate, indicating that snapshot measurements will be insufficient to develop accurate annualized emissions estimates. More importantly, reconciling top-down measurements and bottom-up inventory estimates would be impossible without an understanding of the frequency and duration of emissions events from equipment groups such as tanks. Variations in tank emissions may be caused by process conditions such as the frequency and volume of unloading operations from wells and separators, malfunctioning equipment, or maintenance issues. In addition, ambient temperature and liquid levels in tanks can also affect observed methane emissions. Establishing the bounds of emissions variation through monitoring is key to developing updated emissions inventory estimates. It is hence paramount to effectively estimate the duration and frequency of such intermittent emissions, which requires the use of a high sampling frequency measurement system.

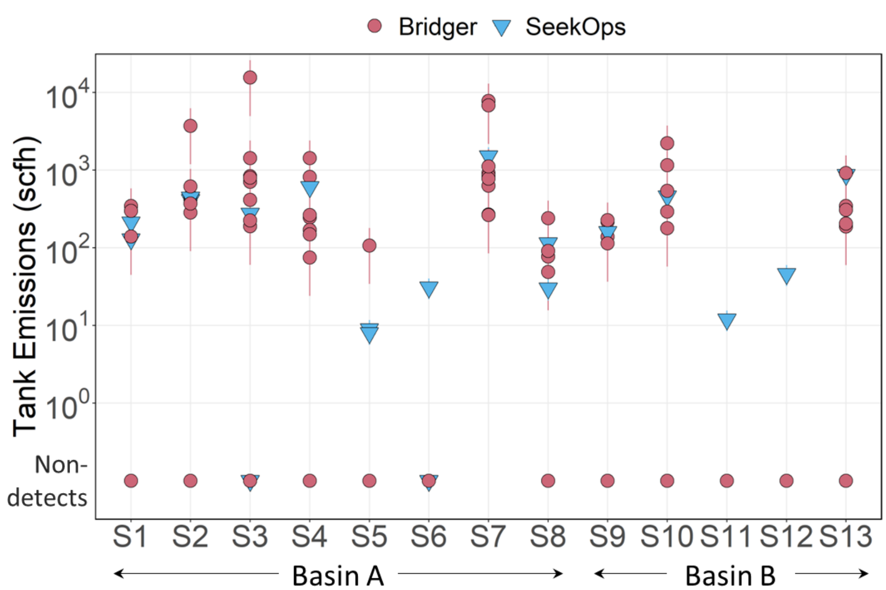


Figure 2: Aggregate tank-level methane emissions measurements by Bridger (red circles) and SeekOps (blue triangles) at all sites in basin A and basin B. Datapoints show both repeat measurements conducted on the same day as well as multi-day measurements at a site. Inventory estimates at these sites are between 40 and 800 scfh (see Figure 1).

The variation in tank emissions shown in Figure 2 is tightly linked to total site-level emissions. Figure 3 shows total site-level emissions in basins A and B, disaggregated by three major equipment types typically seen at upstream production facilities – tanks, gas processing units (GPU), and wellheads. Each column represents a round of measurement by either Bridger or SeekOps. Emissions not associated with these three major equipment categories are classified under 'other' – these can include piping, meters, or other co-located equipment. We make a few important observations. First, emissions vary by about an order of magnitude across basins, with basin A exhibiting significant higher emissions associated with tanks compared to basin B. Second, tank emissions dominate total emissions in both basins, contributing 58% and 50% of total emission in basin A and basin B, respectively. Thus, variability in site-level emissions is dominated by variability in tank-related emissions. Third, basin characteristics can significantly affect the composition of equipment-level emissions. Although tanks contribute the majority of emissions in both basins, GPUs contribute only 14% of total emissions in basin A but 33% of total emissions in basin B. Thus, a non-dominant equipment type in one basin could be a dominant equipment-type in another, underscoring the need to understand basin characteristics to inform measurement and sampling procedures.

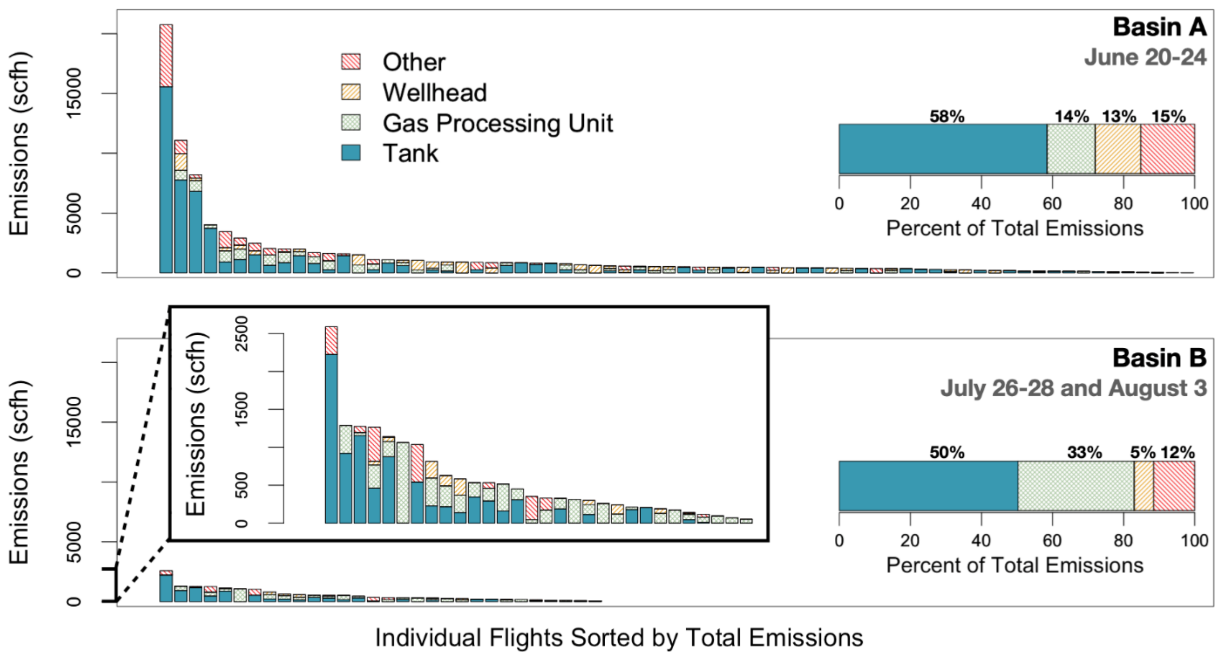


Figure 3: Site-level emissions in basin A (top) and basin B (bottom) disaggregated by three major equipment groups: tanks (turquoise), gas processing units (pale green), wellheads (beige), and other equipment on site (pink). Each bar represents a single round of measurement by either Bridger or SeekOps and is sorted in descending order of site-level emissions. Tanks are the dominant emission source in both basins, although gas processing units contribute a larger share of total emissions in basin B (33%), compared to basin A (14%).

3.3. Intra-day temporal variations

Intra-day variation in methane emissions can be significant. These can arise from process conditions such as separator dumps or liquid levels on tanks, environmental conditions such as ambient temperature, or equipment failure such as broken level indicators and thief hatches. Figure 4 shows time series of same day measurements of tank emissions as recorded by Bridger and SeekOps across basins A and B. Most measurements occurred within a span of 8 hours at each site and varied by over an order of magnitude within a given day. Specifically, Site S3 exhibited the greatest variation with a low measurement below detection threshold and a high measurement of over 15,000 scfh. Follow up with the operator revealed the source of a large emission in basin B to be a stuck dump valve event, with a maximum emission duration of 12 hours before it was fixed. Thus, the ability to identify short duration but high-volume events is critical to develop accurate annualized emissions inventories. Multi-pass measurements with aerial technologies reveal the importance of characterizing intra-day emission variations. The key to explaining any discrepancy between measurements and emission inventory estimates requires an improved understanding of the frequency and duration of emissions from variable sources such as tanks.

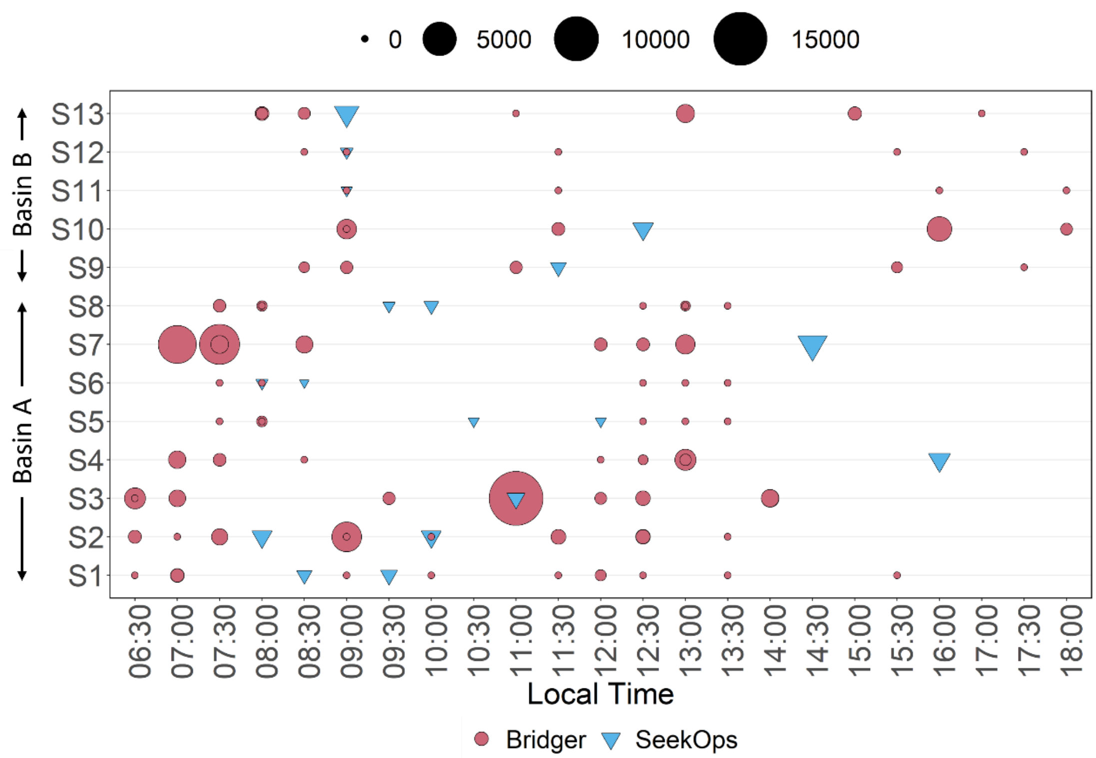


Figure 4. Time series of tank-related methane emissions observed on each site by Bridger Photonics (red circles) and SeekOps (blue triangles), where each row represents a site. The area of the dots represents volume of emissions. All times are in local time of measurement.

3.4. Using continuous emissions monitoring system (CEMS) to estimate frequency and duration of intermittent emission events

Repeated snapshot methane measurements using SeekOps and Bridger technologies demonstrate the importance of understanding the nature of temporal variations to develop accurate annualized inventory estimates. Without data on the frequency and duration of intermittent emissions events, it would be impossible to directly compare methane emissions seen by one or a few top-down snapshot measurements to an annualized inventory. For example, annual average emissions at a site with significant contribution from uncontrolled tank emissions (Figure 3, basin A) will be strongly correlated with the frequency and duration of tank flash emissions. A snapshot aerial or drone-based measurement that happens to capture an intermittent emission event may not provide an accurate annualized emission estimate for the site, as emissions events may be infrequent. This top-down measurement needs to be scaled by the typical frequency and duration of events on the site to make a direct comparison to the annualized inventory.

CEMS provide a means of estimating the frequency and duration of common emission events on a site-by-site basis (see methods and SI section S4.3). These sensors provide near-continuous concentration measurements without needing a human operator. While reliable site-level or equipment-specific emission quantification is still an open problem, current CEMS can act as an indicator for methane emission events. The CEMS used in this study were used as event detection sensors as quantification was not available.

As outlined above, understanding the distribution of methane emission event frequencies and durations is critical for accurate scaling to annualized inventories for production sites. We outline a framework for doing so here and show initial results. First, we use CEMS to record ambient methane concentrations at participating facilities. Typical CEMS technology provides 1-minute averaged data on atmospheric methane concentration, local wind speed, and wind direction. Second, we translate these concentration data into a log of emission events by applying a spike detection algorithm to the maximum concentration reading across sensors on a minute-by-minute basis. Working with the maximum across sensors simplifies the problem by collapsing multiple signals into one while preserving the spikes that we are interested in analyzing. The spike detection algorithm uses a gradient-based method to flag elevated methane concentrations and group them into events, which can be later filtered by their background-corrected amplitude. This algorithm does not distinguish between operational and fugitive events. A detailed description of the spike detection algorithm can be found in the SI section S4.3. Third, after recording a sufficient number of events, we estimate the distribution of time-between-events (referred to as "wait times") and event durations. The advantage of using this probabilistic framework is that the distribution of event wait times and durations can be refined as more data are collected, thereby helping develop custom, site-specific distributions over time. Furthermore, we can use Monte Carlo methods to sample from these empirical distributions and scale the less-frequent top-down measurements that happen to capture intermittent emission events.

Figure 5 shows the empirical distribution of emission event durations and wait times for all emission events identified by the spike detection algorithm using a background-corrected amplitude threshold of 20 parts per million (ppm). This value was selected to isolate concentration spikes that were notably higher than background readings. Note, however, that thresholds from 10-30 ppm were tested, and the conclusions we present here are consistent across thresholds (see SI section S4.2 for details). Also, no CEMS data were collected in Basin C.

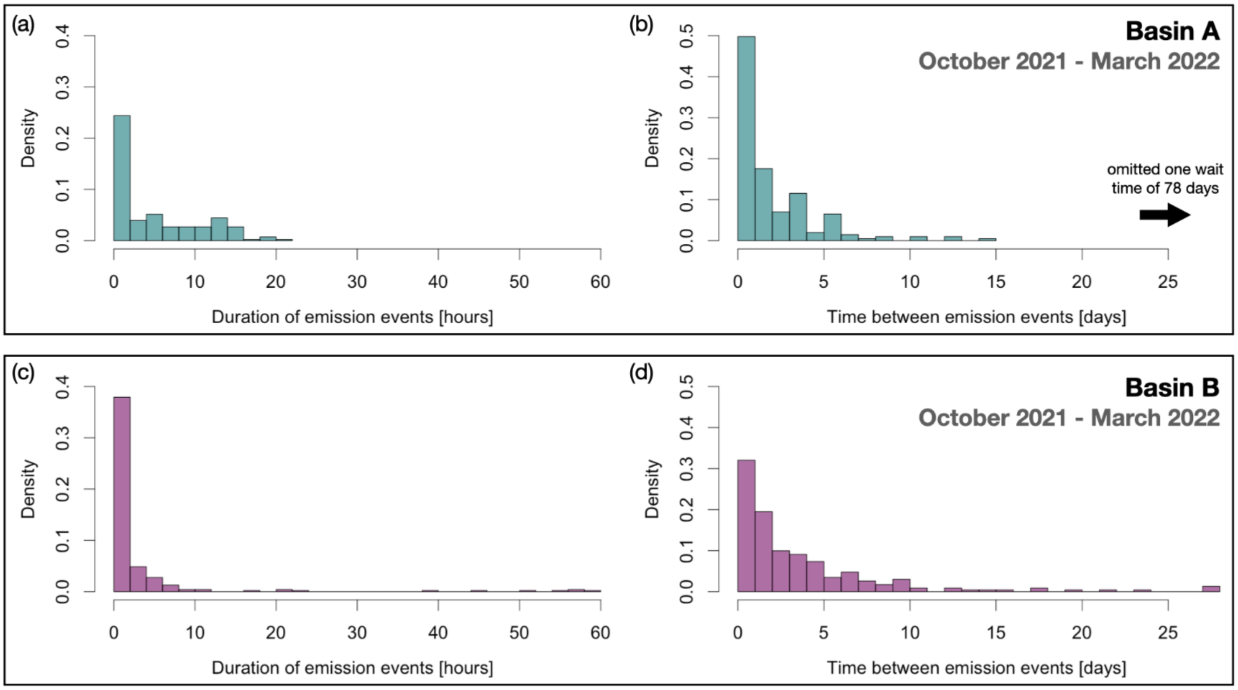


Figure 5. Empirical distributions of emission event durations (Figure 5a and 5c) and wait times (Figure 5b and 5d) between subsequent emission events recorded by CEMS in basin A (top panel, turquoise) and basin B (bottom panel, purple). CEMS data spans October 2021 to March 2022. Note that a wait time of 78 days was omitted from subfigure (b) for visual clarity.

Figure 5 shows that many CEMS-detected emission events are short duration, with 49% of the events from Basin A and 76% of events from Basin B lasting less than 2 hours. Based on operational and supervisory control and data acquisition (SCADA) data from Basin B, many of these short-lived events could be attributed to blowdowns and welldown events. This highlights the importance of high frequency measurements when developing accurate emissions estimates of subsets of an oil and gas supply chain, as monthly or even weekly measurements are likely to miss these short-lived events. While this matters less for basin-level average emissions estimates, it is essential in small sample size applications such as individual supply chains or assessments for small geographic regions. Furthermore, the slightly heavier tail in subfigure (a) compared to subfigure (c) indicates that events (i.e., elevated methane concentrations) tend to last longer in Basin A than Basin B. Finally, subfigures (b) and (d) show that events in Basin A tend to occur more frequently than events in Basin B, with a median wait time between events of 1.1 days in Basin A and 1.9 days in Basin B.

This analysis is currently performed at the site-level and aggregated to the basin-level. As more data are aggregated from each site, the event duration and wait time distributions can be estimated for specific types of emission events such as blowdowns, thief hatch leaks, or liquids unloading events. Using current CEMS technology, this will require operator insight (e.g., operation logs or SCADA data) to translate the list of events into a list of likely sources. This more detailed approach will make the probabilistic scaling framework described above more accurate, as different types of emission events likely have different distributional characteristics. It will also allow for a more detailed root cause analysis of the differences observed across basins in Figure 5. Future work will also use a localization algorithm in conjunction with operator insight to estimate sources for each emission event.

Discussion

Our multi-scale field measurements described here find the following:

(1) Methane emissions in all three basins exhibit significant intraday and daily variation, resulting in a range of three orders of magnitude in snapshot measurements both at the site-level and at the equipment-level,
(2) GHGRP-based inventories, on average, underestimate methane emissions at the basin- and national-level. However, individual sites can have significantly lower emissions than inventory estimates, and
(3) Characterizing operator-specific distributions of the frequency and duration of intermittent emissions events is critical to developing an accurate annualized emissions estimate.

Accurate estimates of average emissions at the basin-level are insufficient for developing target-based policies such as methane fees, methane border adjustment or low leakage certification frameworks. Individual transactions involving natural gas, even at high volumes, can be sourced from a small number of high-producing assets, and there can be significant design, operational and maintenance variation that impacts emissions even within a basin or sub-basin [14], [44]–[46]. In this context, multi-scale measurements of methane emissions have demonstrated the need for a robust approach to improve emissions inventories.

Based on results of this study, we recommend the following four guidelines for measurement protocols to accurately estimate methane emissions and inform mitigation strategies.

1. Snapshot measurements are needed to quantify all methane sources at the equipment- or site-level to help reconcile measurements with inventory estimates. While site-level estimates are sufficient for providing a measurement-based inventory, equipment-level data can help reconcile measurements with inventory estimates and provide data to develop mitigation strategies.
2. Measurements to develop distributions of the frequency and duration of intermittent emissions events are key to annualize any snapshot measurement. Because events can last less than 24 hours, high sampling rate technologies like CEMS will likely be needed to develop these distributions. Though CEMS do not yet provide accurate quantification data, their use as event detectors informs near real-time mitigation strategies.
3. Detailed record-keeping of one-time events, maintenance activities, and upset conditions will help to reconcile measurements with engineering-based inventory estimates and to correlate emissions with specific work-practices enabling development of appropriate mitigation options.
4. Independent verification of measurements and quantified emissions, along with operational data, using transparent, peer-reviewed approaches can enable trust-building with the broader public. This verification must go beyond satisfying a checklist of operator actions but involve academic experts who can provide an independent evaluation of all relevant data.

Several studies have demonstrated that official inventories underestimate average methane emissions [20], [21]. Yet, such inventories are often a major component of any operator or government's climate action plans. These inventories form the official basis for domestic regulations as well as submissions to international collaborations such as the UNFCCC process. Given that, it is important to leverage measurements to reconcile and bridge the gap between measurement-based and engineering-based inventory estimates. While site-specific measurements represent an improvement over existing conventional inventory methods like the GHGRP, snapshot measurements have their own limitations associated with temporal variability in emissions. A major open question in methane science is the distribution and frequency of intermittent emission events. While large sample sizes could make up for temporal variation in developing basin-level emissions estimates, such an approach is inadequate for developing target-based approaches to mitigation policies. Multi-scale measurements at each facility that provide quantitative information on emissions volume and frequency and duration of intermittent events is necessary to identify and update equipment-level or facility-level emissions factors in national inventories. This targeted approach where data from the field is used to continuously update inventory assumptions will help bridge the gap between measurements and inventory estimates over time. Furthermore, such detailed information on intermittent events can also be used to updated process-based models such as the Methane Emissions Estimation Tool (MEET) to better align with observations [47], [48]. As technology – especially CEMS flux algorithms and emissions localization capability – improves, it would be possible to provide real-time estimates of site-level methane emissions that can be used in lieu of engineering-based inventory estimates for each site.

The key to building trust for regulators, investors, and the public in a framework for monitoring methane emissions is through independent, third-party verification. The goal of this verification should encompass both evaluating the validity of direct measurements as well as to provide robust uncertainty bounds on emissions based on operational and maintenance records, emissions and activity data, and an inventory estimate that has been reconciled with measurements. The role of an independent third-party is not only important to provide impartiality, but also the necessary expertise to understand both methane emissions and data analytics. There are several ways to perform verification. One approach would be to undertake multiple snapshot verification measurements, across relevant temporal and spatial scales at a representative group of facilities and compare verification measurements with that of reported emissions estimates [49]. Statistical models can then be used to evaluate if the posterior likelihood of the verification measurement data is consistent, or not, with the reported inventory estimates. Another approach would be to use data from CEMS installed at sites to independently estimate emissions through publicly available modeling tools. Measurement approaches should be based on basin-specific characteristics of methane emissions but the key to effective mitigation is the ability to independently verify emissions estimates.

This work has demonstrated the need for multi-scale measurements, including snapshot measurements and high frequency CEMS to accurately estimate methane emissions. In addition to improving methane emissions estimates, many measurement technologies can identify and reduce methane emissions in the near-term, identifying leaks at the equipment-level and acting as event detectors, that will provide operational as well as climate benefits. While we recognize the challenges of going from zero to multi-scale measurements, operators should consider developing monitoring plans that ramp up over a reasonable period. Technology developments of the past few years have made developing quasi real-time estimates of supply chain methane emissions using networked sensor data in a transparent and trusted manner increasingly likely.

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Supplementary Information for:

Multi-scale Methane Measurements at Oil and Gas Facilities Reveal Necessary Framework for Improved Emissions Accounting

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S.1 Elements of a QMRV protocol

The elements of the quantification, monitoring, reporting, and verification (QMRV) protocol developed as part of this study are outlined in this section. Operators were expected to use this protocol as a guideline to develop site-specific QMRV plans. The protocol is designed to be flexible so operators could choose a technology for methane measurements that best suited the activity and emissions profile of their sites. There are four main elements to the QMRV protocol.

1. Development of a QMRV plan
2. Emissions inventory estimation and reporting
3. Multi-scale emissions monitoring
4. Independent verification

The four elements are summarized in Figure S1 and further described below.

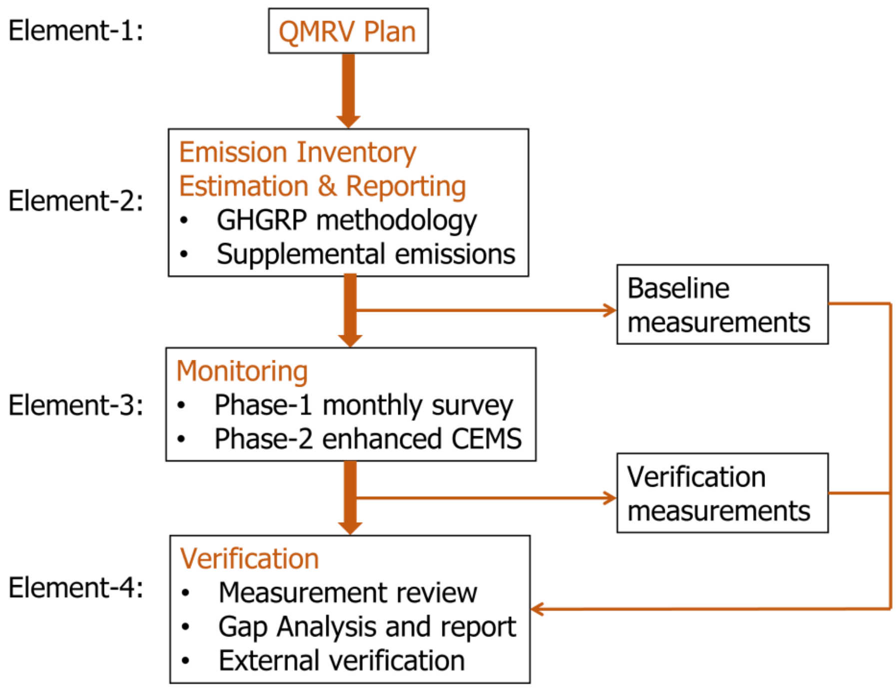

Figure S1. Four major elements of the QMRV plan include (1) preparation of the QMRV plan by the operator, (2) initial inventory and emissions intensity estimation, (3) monitoring that includes periodic surveys (phase-1) and the use of continuous emissions monitoring system (CEMS, phase-2), and (4) verification.

Element 1- Development of a QMRV plan:
The intent of the QMRV plan is to provide operators with the agency to make choices about emissions monitoring, reporting, and verification on their sites, within the guidelines established through this protocol. As part of the QMRV plan, the operator is expected to identify the list of sites along with activity data that are enrolled in the program, specify emissions estimation and reporting methods, including any supplementary emissions data that are typically not included in conventional inventories such as the EPA greenhouse gas reporting program (GHGRP) or those specified by other regulatory agencies such as the Environment and Climate Change Canada. In addition, the operator specifies the technologies that will be used in the monitoring element of the protocol, mitigation methods and work practice standards employed. The total number of sites enrolled in a QMRV program is based on a fixed total production volume. If the enrolled assets are only a fraction of the total assets owned and/or operated by the operator, they should include a list of non-enrolled sites in the basin that are not part of the QMRV plan. This is necessary to

survey non-enrolled assets using top-down measurement approaches to ensure representativeness of the enrolled assets in the QMRV program.

Element 2- Emission Inventory Estimation and Reporting:

For each enrolled site, the operator is expected to calculate and report the operator estimated inventory which includes GHG emissions, GHG emissions intensity and methane emissions intensity by employing methods identified in section S3. These estimates should be based on empirical activity data from the enrolled sites and EPA-specified emissions factors. In addition, the operator should also include supplementary emissions information that account for known deficiencies in the GHGRP such as methane slip from exhaust using AP-42 emissions factors. Finally, other known sources of emissions that are not included in the GHGRP can also be included (see section S3). These include small combustion sources that do not need to be reported, methane emitted for operational activities such as truck-loading, emissions from operational issues such as improperly open thief hatches, improved emissions tracking of blow-through from dump valves, flare and combustor downtimes and inefficiencies, small blowdowns, or compressor starts. The operator must include all emissions from handling of the gas stream, from the enrolled assets at production sites through to central handling facilities, even if the central handling facilities are downstream and away from the well site. As central handling facilities may also handle production from other well sites that are not included in the QMRV program, the operator will only include a portion of the total emissions from these central handling facilities. The fraction of the central handling facility emissions will be in proportion to the gas volumes received from the wells enrolled in the QMRV program. In all cases, the methodology to develop the composite inventory (GHGRP + supplemental inventory, see section S3) should be specified in the QMRV plan and must be maintained throughout the duration of the QMRV program.

Element 3 – Multi-scale emissions monitoring:

Operators will undertake up to two phases of emission measurement and monitoring on all enrolled sites. Phase-1 consists of periodic leak detection and repair (LDAR) surveys using survey-type technologies at a minimum monthly survey frequency. Phase 2 consists of enhanced monitoring using continuous or near-continuous emissions monitoring systems (CEMS) to detect intermittent, high-volume, emission events and to initiate mitigation actions faster than a periodic survey would allow.

Phase-1 monitoring consists of monthly LDAR survey using OGI-based infrared cameras or snapshot approaches such as aerial or drone-based measurements. Any LDAR survey is required to measure all emissions at the facility, not just fugitive emissions or leaks in order to enable comparisons to top-down measurements. These include sources such as storage tanks, compressors, inefficient flares, and pneumatic controllers. Alternative monitoring programs can be proposed by the operator for Phase-1 if they can demonstrate mitigation equivalence with monthly LDAR surveys using models such as FEAST [1]. The operator is expected to maintain detailed records of these surveys including emission events, repairs undertaken, and potential causes for repair delays. In addition, operators are required to conduct weekly surveys using audio, visual, olfactory (AVO) detection, EPA method-21, or other appropriate technology to catch episodic emissions that might occur between the monthly surveys. Phase-1 monitoring should also focus on detecting abnormal methane and CO_2 emissions from the sources at the site. If abnormal emissions are detected during a LDAR survey – regular or informal – the operator must investigate, repair (or otherwise address) any problems, record the survey results and any actions taken, and either measure or estimate total emissions released based on an estimated duration of the emissions.

Phase-2 enhanced monitoring consists of deploying an appropriate CEMS across all enrolled sites. The goal of the Phase-2 monitoring is to capture intermittent and short-duration emission events that can occur between surveys. Recent studies have demonstrated that intermittent emissions contribute significantly to total basin-level emissions [2]. Without a near-CEMS approach to identifying the frequency and duration of such events, snapshot measurements are unlikely to provide an accurate annualized emissions estimate. Furthermore, the distributions of the frequency and duration of intermittent events for each operator and basin can be used to appropriately scale snapshot measurements to estimate annualized emissions. Finally, CEMS data provides real-time verification that high volume emission events are not missed because of gaps in periodic monitoring, allowing third-party verifiers to independently assess emissions estimates. While commercially available CEMS do not yet accurately quantify emissions, they can function as a '*smoke alarm*' to quickly detect and localize high volume emission events. Improvements in CEMS technology in the future could be used to develop real-time estimates of emissions across the natural gas supply chain. Because CEMS technologies are relatively new, operators are requested to evaluate the cost and logistical ease of using these sensors to inform future deployment.

A key aspect of the QMRV plan is that data collected through this multi-scale monitoring approach be made available to the third-party verifier and independent assessor for review as part of the verification process monthly.

Element 4 – Verification:
Independent verification is key to building trust in any QMRV program and includes steps taken by the QMRV program administration, operator, third-party verifier, and independent assessor. Here, verification consists of several steps:

a. Independent baseline emissions measurement conducted by the program administrator at all enrolled sites employing both top-down and bottom-up approaches such as aerial- and drone-based surveys, OGI surveys, and satellite observations. These measurements must be completed before the start of the monitoring phase. If the number of enrolled sites is small compared to the asset portfolio of the operator, <u>the baseline top-down measurements should include emissions quantification at non-enrolled sites to ensure representativeness of sites participating in the QMRV program</u>. The data will be made available to the operator, third-party verifier, and independent assessor.

   The key goals of the baseline measurement phase are as follows:
   - Compare the operator estimated inventory with measurement informed inventory
   - Characterize site emissions, including the frequency of potential super-emitters
   - Correlate the normal and super-emitter emissions with site operations and maintenance records.
   - Inform planning for the rest of the QMRV program, including identification of major sources of emissions, to guide the enhanced monitoring phase.

b. Final end-of-project top-down emissions measurements conducted by the program administrator using the same technologies as the baseline. The data will be made available to the operator, third-party verifier, and independent assessor.

c. A final report by the operator attesting that all measurements and analysis have been conducted in compliance with the QMRV plan. This includes a reconciliation analysis conducted by the operator when the end-of-project measurements are different than the measurement informed inventory estimates by over 50%. This threshold is based on an analysis of typical uncertainties associated with current top-down measurement technologies. This report by the operator will be made available to the third-party verifier and the independent assessor.

d. A 'verification report' prepared by a third-party verifier to assess the validity of baseline and verification emissions measurements and analysis, the final report prepared by the operator, and whether the goals of the QMRV program have been achieved. This verification report will confirm to the QMRV program administrator whether the operator has satisfied the requirements of the program and that the final operator report does not contain data or analysis errors. The third-party verifier can choose to re-analyze all data collected throughout the program if necessary.

e. Finally, the independent assessor will develop an 'Independent assessment report' to synthesize findings from all measurements conducted at enrolled sites, assess monitoring technologies, and provide recommendations for improvements to the QMRV program and scale up across operator's portfolio of assets. The independent assessor may also analyze public data on the enrolled sites (e.g., satellite or other measurements) to compare emissions measured through the QMRV program. The role of the independent assessor, as the name implies, is to independently assess the 'verification report' through data collected as part of the QMRV program as well as any other available data. As such, the independent assessor must have domain knowledge of O&G operations and be an expert in methane data analysis.

S.2 Measurement technologies

S.2.1 OGI camera

The bottom-up survey used optical gas-imaging (OGI) camera paired with Hi-Flow Sampler to detect and quantify emissions. The OGI camera is a common technology used by operators to conduct LDAR surveys because it can localize emissions for future repairs. There are several factors that impact the detection rate of OGI camera, including imaging distance, plume temperature, atmospheric temperature, background, humidity, gas compositions etc. [3] Moreover, recent study by Zimmerle et al. found that the experience of the measuring technician also plays a significant role in emissions detection rate [4]. It is worth noting that OGI cameras has difficulties detecting methane slips due to the high temperatures of vapors [5].

The bottom-up survey included 1-2 measurements of each site and quantified both leak and vent emissions at the component-level. Detected emissions are quantified with Hi-Flow Sampler, where possible. When Hi-Flow Sampler cannot access the emission source, the field crew quantified emissions using visual estimates. Besides emission rates, the field crew collected data on emissions type (leak vs vent), process block, field equipment designation, component, operating mode, gas type, and additional description on emissions. Data are reported in Excel spreadsheets.

S.2.2 Bridger Photonics

Bridger Photonics used advanced light detection and ranging (LiDAR) technology, a downward looking plume identification system, to map out methane emissions. By mounting it on a helicopter or small plane, the system can scan dozens of sites daily, revisit sites with detection in the same day for persistence checks and provide indications of detected emissions. Bridger's technology does not require any observer or operator to be present at the site. However, quantification of detected emissions requires a week or more to produce, and the accuracy of the estimates depend on accuracy of wind data. Johnson et al. tested the uncertainty range of Bridger's technology to be +/- 31 to 68%, depending on the availability of accurate wind data [6].

Bridger conducted 2-3 rounds of measurement of a site every day to collect emissions data. During each round of measurement, Bridger flew over the site 2-3 times within a couple of minutes. Emissions locations are marked by Emissions Location numbers indicating the location of emissions on site. Individual plumes are recorded by "Detection ID". Bridger also recorded data on scan date and time, max concentration (ppm-m), wind speed (mph), persistence rate, latitude, and longitude. Data is reported at flight-level in Excel spreadsheet and in .kmz files and reported at site-level in PDF report with site photos.

S.2.3 SeekOps

SeekOps used a SeekIR methane sensor mounted on a drone and a ground meteorological station to inspect and quantify emissions on site. A drone pilot flies the drone downwind of site equipment to scan for methane emissions. The uncertainty range on emissions estimates is ± 30% [7] and the results take approximately a week to produce. SeekOps' technology requires site access to measure emissions.

SeekOps conducted 1-2 measurements of each site in total. Emissions are reported in PDF format by equipment group as marked on site photos. Additionally, the emissions report contains a wind rose, background levels, and site notes from the field crew. The site notes include emissions details, wind changes during measurement, on-site activities, etc.

S.3 Inventory data

Operators are required to develop an emissions inventory prior to the start of the program, and monthly thereafter through the phase-1 and phase-2 monitoring periods. To standardize inventory reporting, operators are required to use the Environmental Protection Agency's Greenhouse Gas Reporting Program (GHGRP) template and supplement it with sources that are known to be excluded in the GHGRP [8].

GHGRP sources include the following: pneumatic devices, pneumatic pumps, dehydrator vents, well venting for liquids unloading, onshore production petroleum and natural gas gathering and boosting storage tanks, flare stack emissions, reciprocating compressor venting, equipment leak surveys, and supply chain combustion emissions. A detailed list of GHGRP sources, methodology reference, and any associated changes to the GHGRP methodology is shown in Table 1.

Supplemental sources of emissions that are not part of the conventional GHGRP reporting must be separately accounted for in the inventory estimation process. Sources include methane slip in compressor engines, vessel blowdowns, compressor blowdowns, compressor starts, pressure release valve (PRV) venting, produced water tank emissions, combustion emissions from small sources, and any observed emissions as part of the phase-1 and phase-2 monitoring. A detailed list of supplemental sources and associated emissions factors are shown in Table 2.

S.3.1 GHGRP Sources

Table 1: List of source categories in the GHGRP used for inventory calculation for the enrolled sites in the QMRV program, along with any modifications to methodology necessary

Source Categories	**GHGRP Methodology Reference**	**Changes to GHGRP methodology**
Pneumatic devices	40 CFR Part 98.233(a)	• "$Count_t$" limited to enrolled sites • "GHG_i" limited average concentration of methane or CO_2 in enrolled sites • "T_t" limited to operating hours for the duration of the QMRV program
Pneumatic pumps	40 CFR Part 98.233(c)	• "$Count_t$" limited to enrolled sites • "GHG_i" limited average concentration of methane or CO_2 in enrolled sites • "T" limited to operating hours for the duration of the QMRV program
Dehydrator vents	40 CFR Part 98.233(e)	• For calculation methodology 1, "hours operated" limited to operating hours for duration of the QMRV program
Well venting for liquids unloading	40 CFR Part 98.233(f)	• "W" limited to enrolled sites • "V_p" limited to liquid unloading events for the duration of the QMRV program

Gathering and boosting storage tanks	40 CFR Part 98.233(j)	• For calculation methods 1 and 2,
		  ○ "$E_{s,i,o}$" limited to enrolled sites
		  ○ "E_n" limited to flare stack emissions from enrolled sites

		○ "T_n" limited to the operating hours for duration of the QMRV program • For calculation method 3, ○ "$E_{s,i}$" limited to enrolled sites ○ "Count" limited to enrolled sites
Flare stack emissions	40 CFR Part 98.233(n)	• "E_s" limited to enrolled sites
Reciprocating compressor venting	40 CFR Part 98.233(p)	• "Count" limited to enrolled sites • "$EF_{i,s}$" limited to the average concentration of methane or CO_2 in enrolled sites
Equipment leak surveys[1]	40 CFR Part 98.233(q)	• "GHG_i" limited average concentration of methane or CO2 in enrolled sites • "X_p" limited to enrolled sites • "$T_{p,z}$" limited to operating hours for the duration of the QMRV program
Combustion emissions (production, gathering and boosting, distribution)	40 CFR Part 98.233(z)	• For Tier-2 calculation methodology in 40 CFR Part 98.33(a) and 98.33(c)(2): ○ "CO_2" limited to enrolled sites ○ "CH_4" limited to enrolled sites ○ "N_2O" limited to enrolled sites ○ "Fuel" limited to the operating hours for duration of the QMRV program

[1]In some cases, leaker factors may be generated from supplemental sources to replace factors from Table W-1E of subpart W.

S3.2. Supplemental Sources

1. Methane slip in compressor engines

GHG emissions from reciprocating compressor engines can be estimated using the appropriate methane emissions factor from the AP 42 emissions factors [9]. The emissions factors in Table 2 will be substituted in place of the methane emissions factor from Table C-2 of Subpart C in the GHGRP.

Table 2: Supplemental emissions factors for methane slip in compressor engines.

Engine Type	**Pollutant**	**Emission Factor (lb/MMBtu) (fuel input)**	**Emission Factor (kg/MMBtu) (fuel input)**
Uncontrolled emission factors for 2-stroke lean-burn engines	Methane	1.45E+00	6.58E-01
Uncontrolled emission factors for 4-stroke lean-burn engines	Methane	1.25E+00	5.67E-01
Uncontrolled emission factors for 4-stroke rich-burn engines	Methane	2.30E-01	1.04E-01

2. Vessel blowdowns, compressor blowdowns, compressor start, and pressure release valves

GHG emissions for these supplementary source categories can be estimated using the ONE Future methane intensity protocol methodology and the appropriate GHGI emission factor as shown in Table 3 [10]. The emissions factors must be multiplied by the activity data (count of vessels, count of compressors, count of PRVs) to estimate total emissions.

Table 3. Supplemental emissions factors based on the ONE Future methane intensity protocol methodology

Activity	**Units**	**Average CH_4 EF (2019, Table 3.6-2)**	**Average CO_2 EF (2019, Table 3.6-12)**
Vessel blowdowns	kg/vessel	1.6	0.2
Compressor blowdowns	kg/compressor	76.9	8.5
Compressor start	kg/compressor	172.1	19.1
Pressure release valve	kg/PRV	0.7	0.1

3. <u>Produced water tank emissions</u>

Greenhouse gas emissions from produced water tanks that are not controlled by a flare or combustor are generally not reported under the GHGRP. Emissions from produced water storage tank flashing, working, breathing, and loading will be estimated as a supplemental source for the QMRV program. These can be estimated using ProMax simulation software which incorporates estimation equations from the EPA's AP-42 chapter 7 on liquid storage tanks [9, p. 42].

4. <u>Flares, glycol dehydrators</u>

Emissions from flares and glycol dehydrators can be estimated directly using methods specified by the oil and gas methane partnership (OGMP) 2.0 or the EPA GHGRP [11], [12]. All assumptions, inputs, and software tools used in this estimation must be documented.

5. <u>Combustion emissions from small sources</u>

GHG emissions from external combustion sources with a heat rating less than 5 MMBtu per hour and internal combustion sources with a heat rating of less than 1 MMBtu per hour are exempt from emissions calculations under the GHGRP. For the purposes of the QMRV program, GHG emissions from these small combustion sources will be estimated using the same calculation methodologies in 98.233(z) of the GHGRP.

6. <u>Observed emissions</u>

Observed emissions during the monitoring phase (phase 1 and phase 2) of the QMRV program can be estimated based on one or more of the following methods. The operator will select the most appropriate method for emissions estimation and document which method is used.

- Emission rates for similar components or equipment as measured during the baseline emissions survey at enrolled sites
- Emissions rates estimated by continuous monitoring technology (Phase 2 only)
- Employ emission factors based on Table 4 for sources not well represented in the GHGRP

Table 4. Leaker emissions factors for observed emission sources not well represented in the GHGRP. All emissions factors are based on values in Zimmerle et al. [13].

Source	Emissions Factor (scfh)
Tank vent (common multi-unit)	109.0
Tank vent (common single-unit)	43.7
Thief hatch	25.9
Rod packing vent (operating)	24.9
Rod packing vent (not operating, pressurized)	20.1
Rod packing vent (not operating, depressurized)	9.3

S.4 Measurement Methodology

S.4.1 Snapshot measurement data

Bridger's data is analyzed at the emitter (Emissions Location) level. First, based on the scan date and time in the Excel spreadsheet and the .kmz file, we grouped each overflight into rounds of measurements undertaken by Bridger. Next, we calculate the average emissions rate for each Emissions Location in that round of measurements. Finally, Emissions Location from the same round of measurements were added together to represent site-level emissions rate for that round of measurement. Bridger conducted 2-3 rounds of measurements each day.

SeekOps measured emissions at equipment group level. Site-level emissions was calculated by summing equipment group level emissions. SeekOps conducted 1-2 measurements of each site during the study. The equipment identification provided by SeekOps' report provided a good reference for emissions attribution. By comparing Bridger's site photos against SeekOps', we were able to identify emitting equipment measured by Bridger.

Each measurement from Bridger and SeekOps was considered an independent estimate of emissions that best represented each site's emissions at the time of measurement. Due to the fluctuations in equipment emissions, there was no certain time that best represents the sites' emissions. As a result, every measurement was considered equally valid, and the average of all rounds of measurement from Bridger and SeekOps was taken as the best representation of site-level emissions. Basin-level emissions are calculated as the average of site-level emissions in the basin.

We did not independent conduct any tests of technology performance because prior peer-reviewed studies demonstrate the fundamental characteristics of Bridger and SeekOps systems [6], [14]. The uncertainties used in the analysis are based on these peer-reviewed studies. However, we note that the uncertainties presented in this analysis are conservative estimates and do not account for higher sample sizes in our study that will reduce aggregate uncertainty [15].

S.4.2 OGI baseline measurement data

Equipment- and site-level emissions were calculated by summing component-level emissions. OGI survey conducted 1-2 measurements of each site during the study. The limitation of OGI camera paired with Hi-Flow Sampler is discussed in Section S.2.1. Equipment- and site-level emissions for each basin is listed below. In Table 5, we show equipment-level emissions comparison for major equipment groups as measured by OGI, SeekOps, and Bridger for Basin A and Basin B. Equipment-level comparison is unavailable for Basin C due to operator restrictions. Average equipment-level emissions are calculated as the average of all rounds of measurement taken by each technology.

Table 5: Equipment-level emissions comparison

Basin	Equipment	OGI (SCFH)	Bridger (SCFH)	SeekOps (SCFH)
Basin A	Tanks	104	657	271
Basin A	Wellheads	6	139	89

Basin A	GPU/Separator	19	157	38
Basin B	Tanks	95	228	311
Basin B	Wellheads	8	26	25
Basin B	GPU/Separator	91	148	201

In Table 6, we show site-level emissions comparison as measured by OGI, SeekOps, and Bridger for basin A, basin B, and basin C. Average site-level emissions is calculated as the average of all rounds of measurement taken for each site by each technology. Bridger did not measure 2 enrolled sites in basin C due to wrong coordinates. Consequently, the site-level emissions comparison of basin C excludes these 2 enrolled sites.

Table 6: Site-level emissions comparison

Basin	OGI (scfh)	Bridger (scfh)	SeekOps (scfh)
Basin A	131	1153	696
Basin B	199	448	638
Basin C	51	432	184

At the equipment-level, Bridger and SeekOps technologies measure up to an order of magnitude more emissions than the OGI +Hi-Flow measurement. While the OGI survey also notes that tanks as a major contributor to emissions, measured tank emissions by the Hi-Flow instrument are significantly lower than that by Bridger and SeekOps. At the site-level, OGI+Hi-Flow system constantly measured less emissions than Bridger and SeekOps. Due to the limitations of OGI camera discussed in section S.2.1, measurements from OGI are not included in the calculation of measured emissions.

S.4.3 Continuous emissions monitoring systems (CEMS)

Continuous emissions monitoring systems (CEMS) were deployed on several assets enrolled in the QMRV program. These sensors record ambient methane concentrations at their location, which is typically at the fence line or next to equipment with high potential for methane emissions. Using these concentration measurements to estimate emission source locations and rates is a complicated problem, and while some CEMS vendors have preliminary tools for doing so, these location and rate estimates were not made fully available due to their experimental nature. Therefore, we only consider concentration data in this paper.

In section 3.4 of the main text, we propose a framework for better understanding the distribution of emission event durations and wait times using CEMS concentration data. These distributions provide insight into emission characteristics at the basin-level and can be used to scale snapshot top-down measurements that happen to capture an episodic event (e.g., liquids unloading or blowdown events) to make a direct comparison to an annualized inventory. This framework depends on an algorithm that translates concentration data into a list of emission events and their corresponding start times and durations.

At a high level, the algorithm flags spikes in a methane concentration time series that we believe to be the result of activity on the site and returns their start time and duration. The algorithm operates on univariate time series only. In section 3.4 of the main text, we apply it to the maximum methane concentration across sensors deployed on a single site on a minute-by-minute basis. This simplifies the problem, as it collapses the data from each sensor into one signal that preserves the spikes that we wish to analyze. Because we are interested in spikes that are the result of site activity, we do not target gradual changes in methane concentration (i.e., shallow bumps), but rather sharp increases (i.e., spikes), as we have found that methane emissions typically result in rapid increases in ambient concentrations above baseline.

The type of events that are flagged by the algorithm depend largely on three parameters:

1. The **going up threshold** is used to flag rapid increases in methane concentration and trigger the start of an event. The default value is 0.25ppm. Note that this parameter is scale dependent.
2. The **return threshold** is used to determine when an event has ended. The default is 10% of the maximum event concentration. Note that this parameter is scale independent.
3. The **amplitude threshold** is used to filter out events that are too small after considering background concentrations. Note that this parameter is scale dependent.

The algorithm proceeds as follows. First, input a univariate time series (i.e., the methane concentration data) and take the first order difference. Flag positive differences greater than the **going up threshold**. These time steps are recorded and will be used later to indicate the start of an event. Call these points the **event start times**. Next, initialize a Boolean **event flag** to FALSE, and then loop through each time step in the time series. At each time step, do the following:

- If not already in an event (i.e., **event flag** is FALSE) and:
  - If this time step is an **event start time**, enter an event (i.e., set **event flag** to TRUE). The time series will remain in the event until the event exit conditions are met.
  - If this time step is not an **event start time**, do nothing.
- If already in an event (i.e., **event flag** is TRUE) and:
  - If the methane concentration at this time step has returned to **return threshold** percent of the maximum concentration recorded during this event, exit the event (i.e., set **event flag** to FALSE).
  - If the methane concentration at this time step has not returned to **return threshold** percent of the maximum concentration recorded during this event, remain in the event.

This methodology provides a mask that covers the duration of each event in the time series. Note that the **return threshold** is defined as a percent of maximum concentration rather than a negative difference because we have found that while events almost always start with a rapid increase in concentrations, they sometimes dissipate at a slower rate. By using this methodology, we impose the following definition of an event: time steps following (and including) the **event start times** up until the methane concentration has returned to **return threshold** percent of the maximum concentration recorded during that event. Looping once through the time series in this manner results in a list of flagged events. Next, loop through these events. For each event, do the following:

- Fit a LOESS curve to the methane concentration data that have not been flagged as an event in a local region surrounding the event. By default, the algorithm uses 120 observations on each side of the event.
- Using the LOESS fit, predict methane concentrations at the time steps that were flagged as the event. This gives an estimate of the local background methane concentrations.
- The amplitude of this event is computed as the maximum methane concentration of the event minus the corresponding background estimate from the LOESS fit.
- Discard the event if the event amplitude is less than the **amplitude threshold.**

This step allows us to filter events by their background-corrected (or background removed) amplitude. The output of this algorithm is a list of events along with their start times and durations. The start time is simply the first time step of the event. The event duration is the difference between the last time step and the first time step. These fields allow us to compute the time between events as the difference between the start time of one event and the last time step of the preceding event.

Note that while this algorithm depends on several hand tuned parameters, these parameters are designed to balance each other out. Specifically, the **going up threshold** is by default set to a small value to catch spikes that build up slowly. The **amplitude threshold** can then be set to a large value to throw out any spikes that did not end up being large enough to be deemed significant. This ensures that no spikes are missed and that only large or significant events are returned. Additionally, we check for events that contain four differences in a row below 0.4ppm, indicating that the event has returned to baseline without triggering the **return threshold**. In these rare cases, we discard the event.

We use an **amplitude threshold** of 20ppm in section 3.4 of` the main text. To provide intuition on the type of events that are flagged with this threshold, we plot the minute-by-minute maximum methane concentration across sensors on a single site enrolled in the QMRV program in Figures S2-S7. The data ranges from October 2021 to March 2022, and we plot each month in a separate figure. Colored lines indicate a flagged event, with different colors corresponding to different events (the colors have no other meaning).

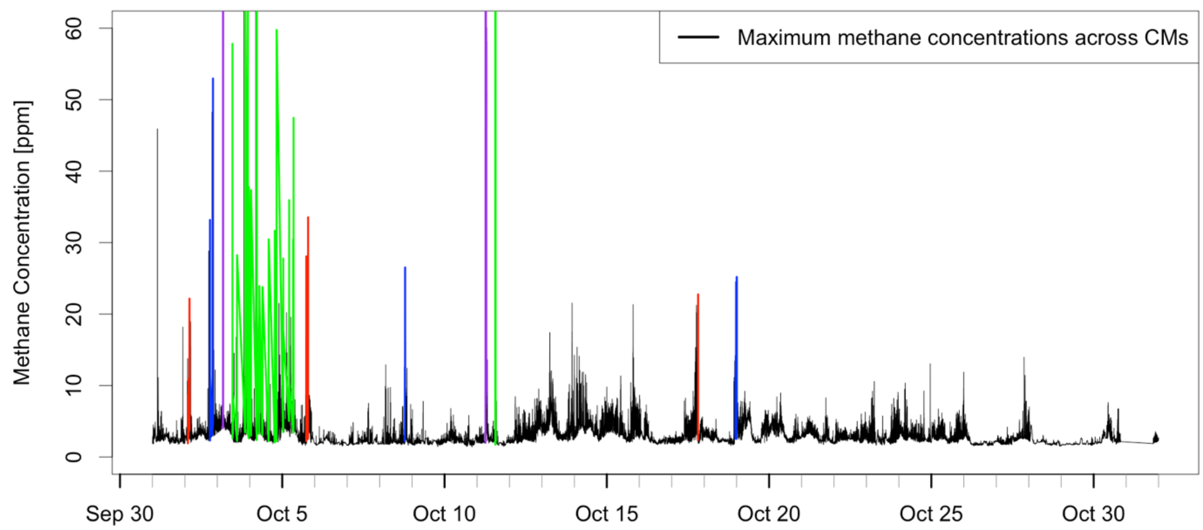

Figure S2. Maximum methane concentration recorded across sensors on a single site enrolled in the QMRV program for October 2021. Note that the vertical axis is restricted to [0,60] to show detail. Spikes flagged by the spike detection algorithm are highlighted in color, with different colors indicating different events.

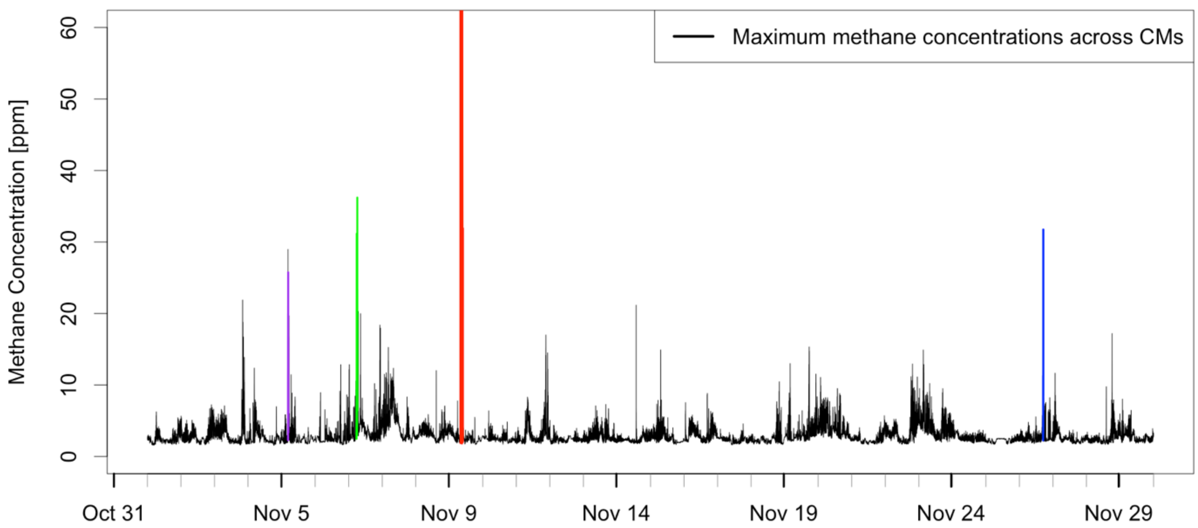

Figure S3. Maximum methane concentration recorded across sensors on a single site enrolled in the QMRV program for November 2021. Note that the vertical axis is restricted to [0,60] to show detail. Spikes flagged by the spike detection algorithm are highlighted in color, with different colors indicating different events.

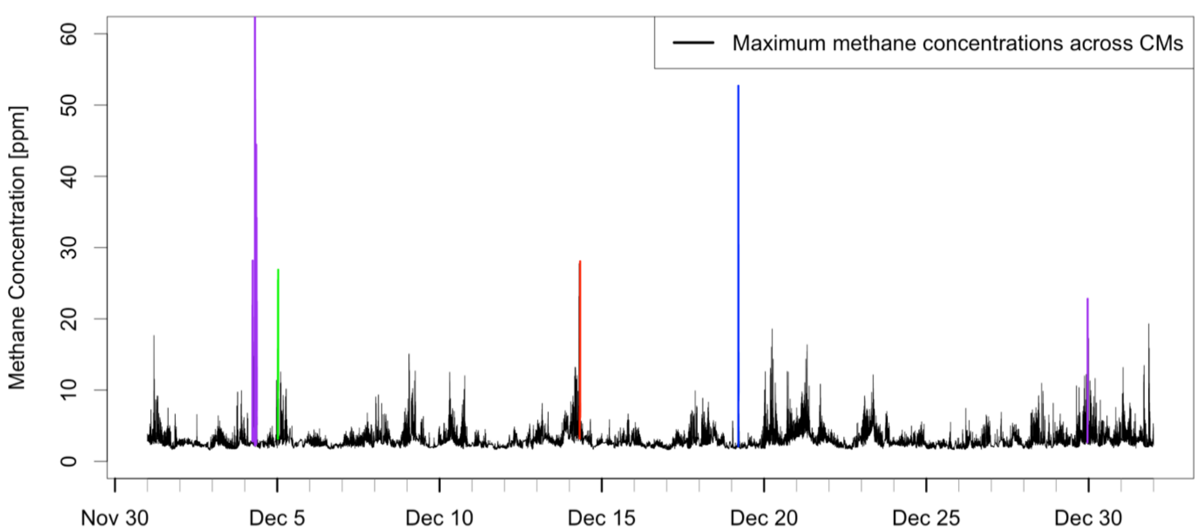

Figure S4. Maximum methane concentration recorded across sensors on a single site enrolled in the QMRV program for December 2021. Note that the vertical axis is restricted to [0,60] to show detail. Spikes flagged by the spike detection algorithm are highlighted in color, with different colors indicating different events.

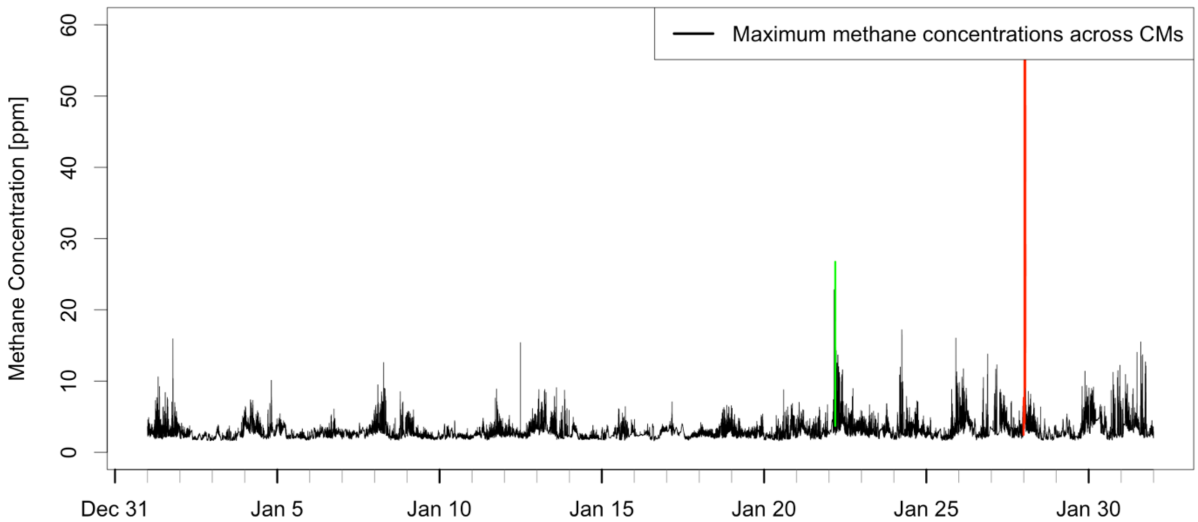

Figure S5. Maximum methane concentration recorded across sensors on a single site enrolled in the QMRV program for January 2022. Note that the vertical axis is restricted to [0,60] to show detail. Spikes flagged by the spike detection algorithm are highlighted in color, with different colors indicating different events.

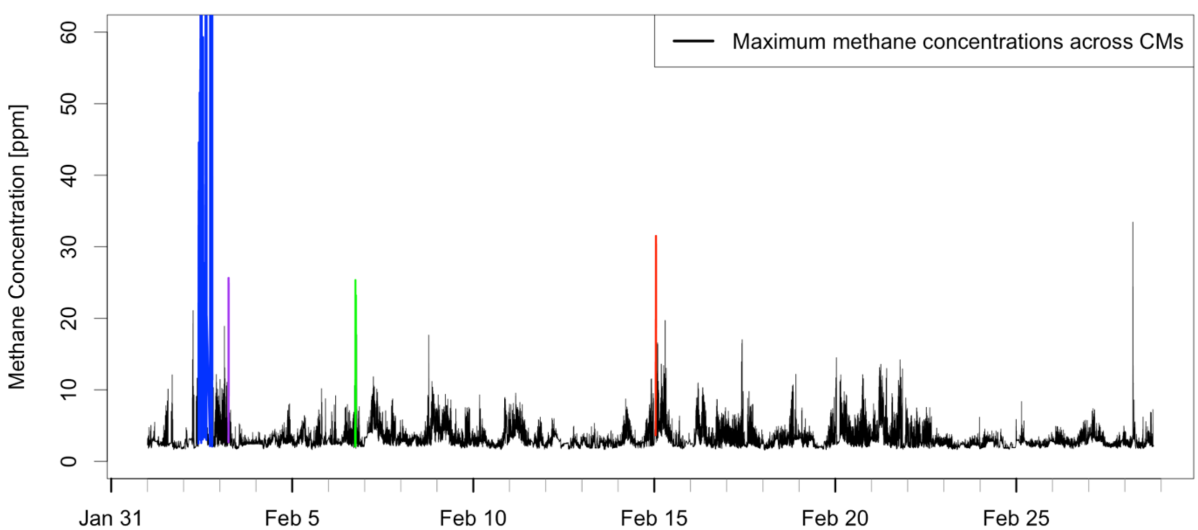

Figure S6. Maximum methane concentration recorded across sensors on a single site enrolled in the QMRV program for February 2022. Note that the vertical axis is restricted to [0,60] to show detail. Spikes flagged by the spike detection algorithm are highlighted in color, with different colors indicating different events.

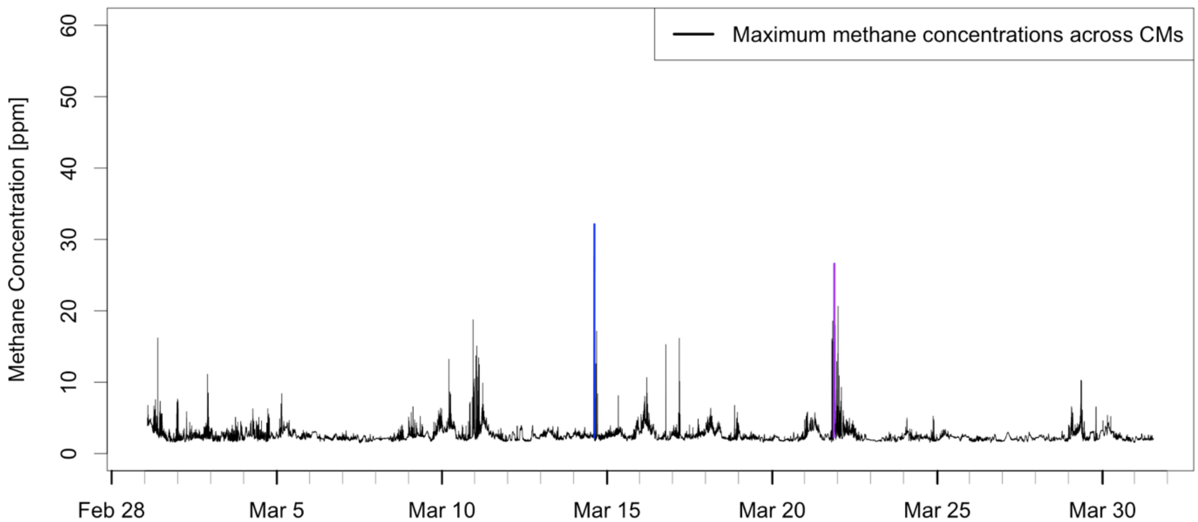

Figure S7. Maximum methane concentration recorded across sensors on a single site enrolled in the QMRV program for March 2022. Note that the vertical axis is restricted to [0,60] to show detail. Spikes flagged by the spike detection algorithm are highlighted in color, with different colors indicating different events.

There are rare instances in which the spike detection algorithm does not detect a notable spike (e.g., October 1, 2021, and February 28, 2022). In future work we will improve the logic used in this algorithm to eliminate these errors.

Finally, we test a range of **amplitude thresholds** (10, 15, 20, 25, and 30ppm) to ensure that the conclusions we present in the main text are not threshold dependent. We find consistent results across thresholds. Specifically, for all tested thresholds:

- A large portion of the events in both basins last less than 2 hours.
- Events in Basin A tend to last longer than events in Basin B (indicated by a heavier tail in subfigures (a) compared to subfigures (c)).
- Events in Basin A tend to occur more frequently than events in Basin B (indicated by a lower median in subfigures (b) compared to subfigures (d)). This is true for the smallest amplitude threshold but is more apparent in the larger thresholds.

For transparency, we show the event duration and wait time histograms for each threshold tested in Figures S8-S12.

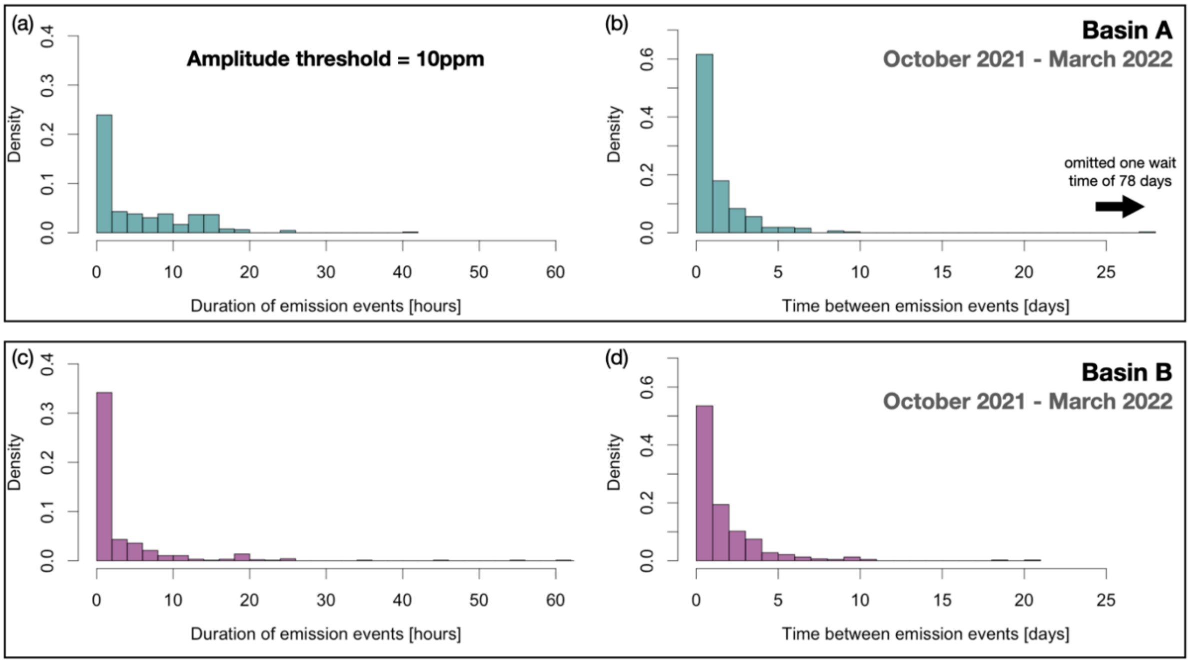

Figure S8. Empirical distributions of emission event durations (a and c) and wait times (b and d) between subsequent emission events recorded by CEMS in basin A (top panel, turquoise) and basin B (bottom panel, purple). CEMS data spans October 2021 to March 2022. Events identified using a spike detection amplitude threshold of 10 ppm.

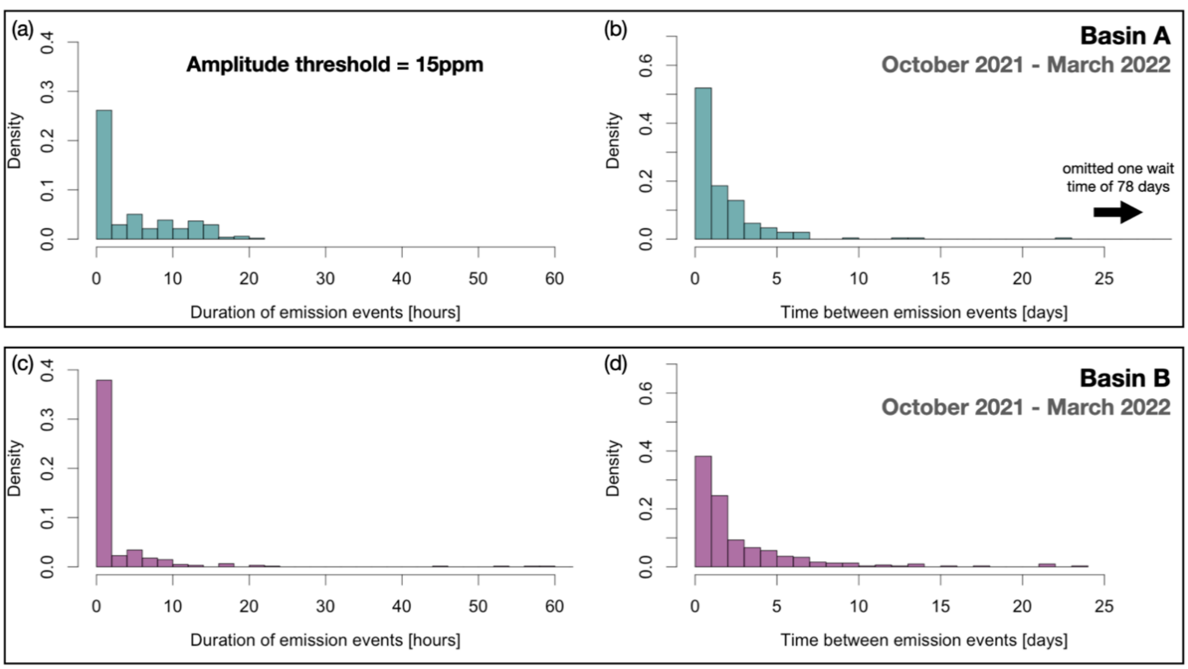

Figure S9. Empirical distributions of emission event durations (a and c) and wait times (b and d) between subsequent emission events recorded by CEMS in basin A (top panel, turquoise) and basin B (bottom panel, purple). CEMS data spans October 2021 to March 2022. Events identified using a spike detection amplitude threshold of 15 ppm.

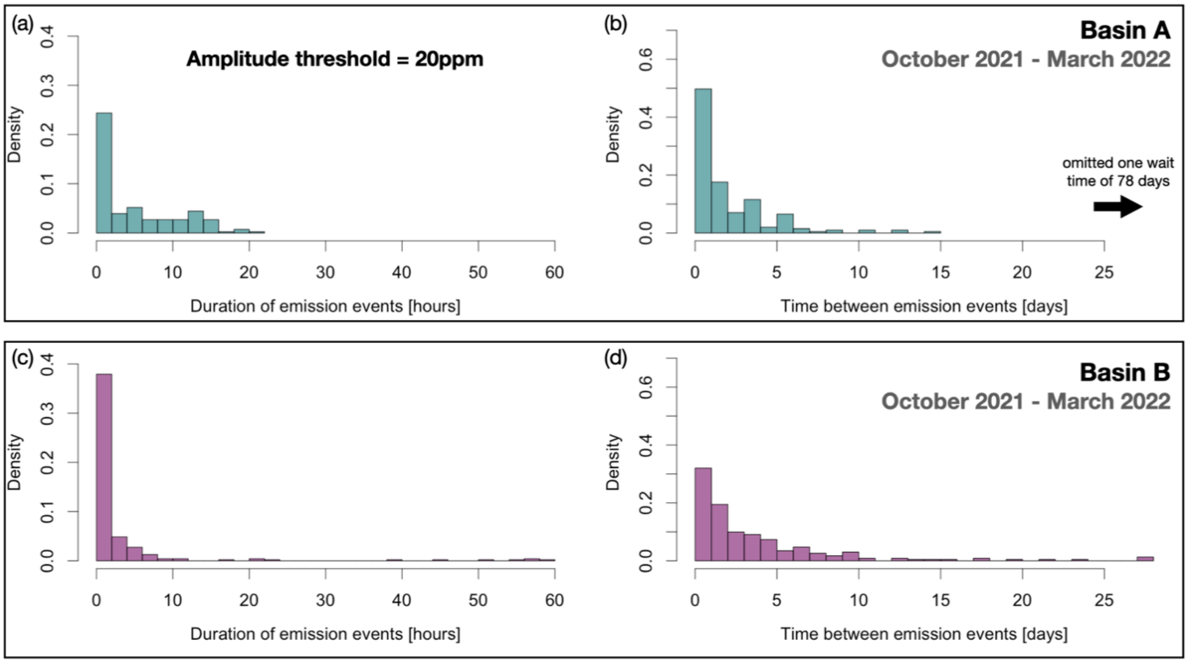

Figure S10. Empirical distributions of emission event durations (a and c) and wait times (b and d) between subsequent emission events recorded by CEMS in basin A (top panel, turquoise) and basin B (bottom panel, purple). CEMS data spans October 2021 to March 2022. Events identified using a spike detection amplitude threshold of 20 ppm.

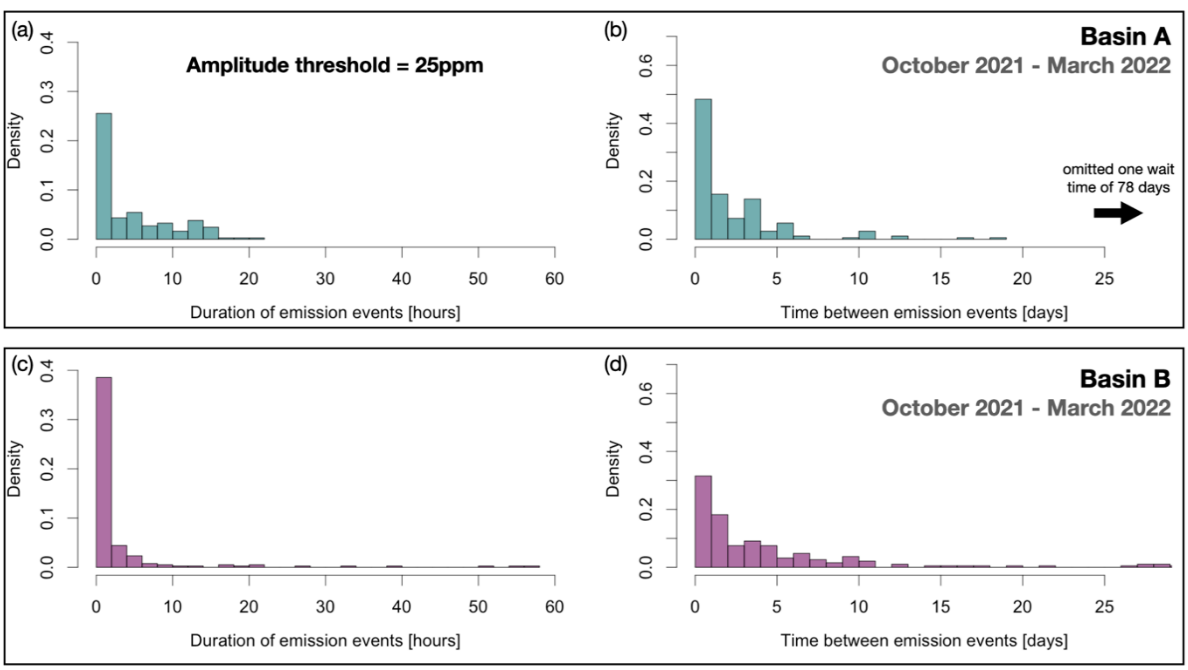

Figure S11. Empirical distributions of emission event durations (a and c) and wait times (b and d) between subsequent emission events recorded by CEMS in basin A (top panel, turquoise) and basin B (bottom panel, *purple). CEMS data spans October 2021 to March 2022. Events identified using a spike detection amplitude threshold of 25 ppm.*

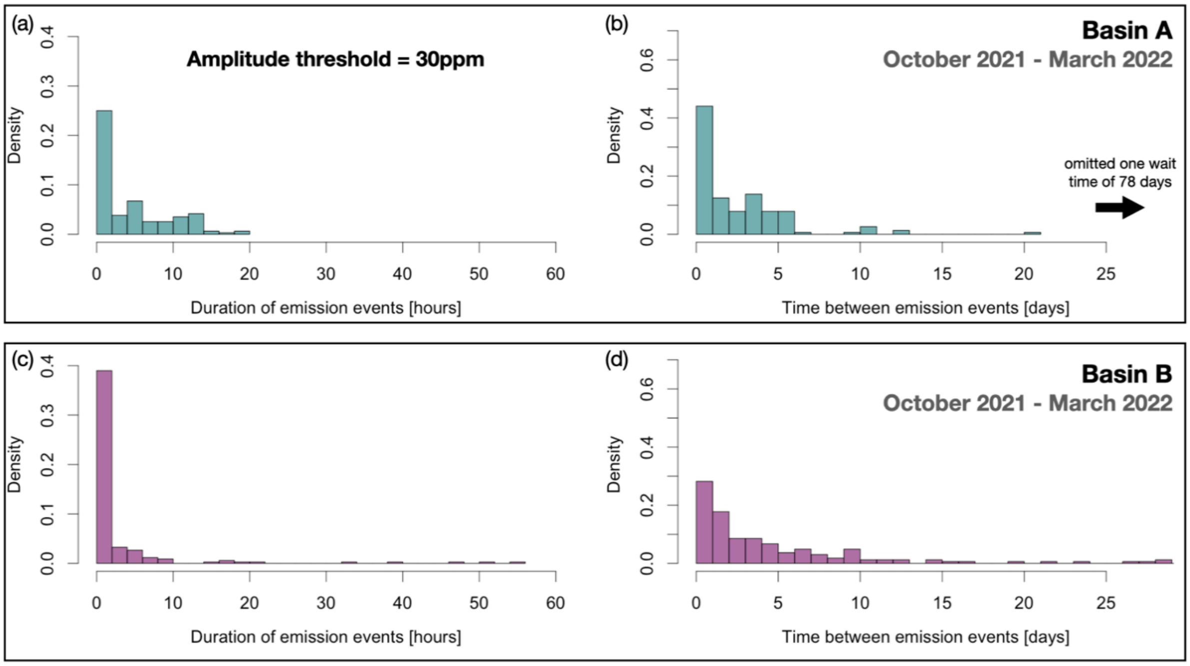

Figure S12. Empirical distributions of emission event durations (a and c) and wait times (b and d) between subsequent emission events recorded by CEMS in basin A (top panel, turquoise) and basin B (bottom panel, purple). CEMS data spans October 2021 to March 2022. Events identified using a spike detection amplitude threshold of 30 ppm.

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