# Multiscale Methane Measurements at Oil and Gas Facilities Reveal Necessary Frameworks 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. Recent legislation in the United States requires updating current methane reporting programs for oil and gas facilities with empirical data. While technological advances have led to improvements in methane emissions measurements and monitoring, the overall effectiveness of mitigation strategies rests on quantifying spatially and temporally varying methane emissions more accurately than the current approaches. 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 emission events. We find that site-level emissions exhibit significant intraday and daily emission variations. Snapshot measurements of methane can span over 3 orders of magnitude and may have limited application in developing annualized inventory estimates at the site level. Consequently, while official inventories underestimate methane emissions on average, emissions at individual facilities can be higher or 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, are key to an 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.

**KEYWORDS:** methane emissions, MRV framework, continuous monitoring systems, oil and gas, certification
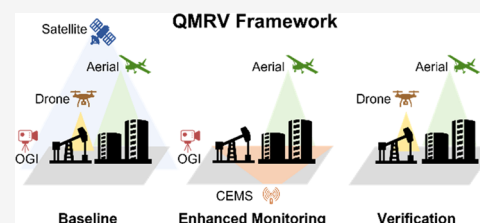
## 1. INTRODUCTION

Reducing methane emissions from the oil and gas (O&G) supply chain is a key component of near-term climate action.[1] More than 100 countries have pledged to reduce methane emissions by 30% by 2030 as part of the United Nations 2021 Conference of Parties.[2] The Inflation Reduction Act (IRA) imposes a methane fee on oil and gas facilities emitting above a certain methane intensity threshold.[3] The CHIPS and Science Act authorizes the establishment of a Center for Greenhouse Gas (GHG) Measurements, Standards, and Information to improve spatially and temporally resolved GHG measurements.[4] 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.[5−7] 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 emission estimation.[8] 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.[9]

Recent advances in methane measurement technology have improved our understanding of methane emissions.[10−14] Large-scale ground and aerial surveys in the Permian Basin demonstrate the importance of identifying intermittent super-emitters.[15,16] 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.[16] A detailed study of temporal variations in methane emissions suggests the potential impact of measurement time on emission estimates, where one-time events like liquids unloading preferentially occur during certain periods of the work-day.[17−20] The effectiveness of and trust in approaches to address methane emissions, therefore, depend on the availability of accurate methane emission 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 emission factors.[21] Analysis of recent field measurements across O&G production facilities in the United States and Canada shows that, on average, measured emissions are ~60% higher than official inventory estimates.[22,23] This is because engineering-based methods rely on component-level activity and emission factors that are often outdated or poorly characterized and emissions from high-emitting or super-emitting events are not accounted for.[21,24] A decomposition study of this discrepancy between measurements and inventory pointed to an underestimation of emission factors associated with tanks and equipment leaks.[21] 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.[9,25−27] Furthermore, intraday variations in emissions from specific equipment like tanks have also been observed.[18] Thus, except in simple site configurations, low-frequency snapshot measurements tend to have high variability and are unsuitable for asset-level differentiation. Advances in technologies such as continuous emission monitoring systems (CEMS) could provide the high-resolution data needed to characterize temporal variability in methane emissions.[28−30] Recent research has also shown a systematic variation in emissions over time as wells get older and the compositions of oil, gas, and liquids change.[31,32] 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 at the site level, measurements require high temporal resolution to detect and quantify intermittent emission events.[31,33]

Many jurisdictions have used leak detection and repair (LDAR) programs to mitigate methane emissions from O&G operations.[34−36] Recent randomized controlled experiments suggest that these programs are effective in reducing fugitive methane emissions.[37,38] 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.[21,39,40] These abnormal emissions have limited or no "monitoring" benefits from typical annual or biannual LDAR programs nor can they reliably be independently verified solely by top-down aerial or drone monitoring methods due to the low sampling frequency. Yet, accurate estimation of these abnormal emissions is important for emission assessment for subsets of oil and gas supply chains. No currently existing technology is sufficient on its own to capture the temporal fluctuations of methane emissions, which is necessary to develop accurate annual emissions estimate.

Under the conventional engineering-based inventory development methods, all operators are required to use identical national-level emission factors that limit operator differentiation 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 reduce emissions. The Inflation Reduction Act (IRA) directs the U.S. Environmental Protection Agency (EPA) to update the current engineering-based reporting requirements with empirical measurement-based data to reflect methane emissions from the reporting facilities accurately.[3] However, no empirical measurement protocol has been demonstrated to provide reasonably accurate supply chain-specific methane emission estimates necessary to assess target-based emission reduction claims. The U.S. federal government has created an interagency task force to identify and deploy tools to measure, monitor, report, and verify GHG emissions.[5] Yet, currently available frameworks do not provide the level of transparency and rigor to build trust among the public through independent, third-party verification.

The significance of accounting for spatial and temporal variations in emissions through multiscale, contemporaneous measurements has been documented in the literature.[18,41] In this work, using multiscale 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 for emissions mitigation. Through this multibasin field study, we describe how a measurement framework that accounts for spatial and temporal variations in methane emissions can help improve 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 emission estimation across the supply chain.

## 2. METHODS

The multiscale 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 improved inventory estimates. These elements include emissions quantification through multiscale 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 Supporting Information (see 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 beginning of the study and an enhanced monitoring phase that involved the 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 more than 0.4 billion cubic feet per day (bcfd) in the aggregate. The QMRV project consisted of three phases: baseline emissions measurements with multiscale methods, enhanced monitoring using CEMS for a period of 6 months, and end-of-project aerial snapshot measurements (Section S1). We deployed four snapshot emission measurement technologies concurrently at these enrolled facilities during the baseline phase and two CEMS technologies for continuous monitoring during the 6 months of enhanced monitoring phase.[6]

The snapshot measurements include an optical gas imaging (OGI) camera paired with a Hi-Flow Sampler, a drone-based mass balance technology by SeekOps, Inc. ("SeekOps"), an aerial LiDAR plume identification system 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.[10,42−44] In addition, GHGSat conducted satellite measurements concurrently at the
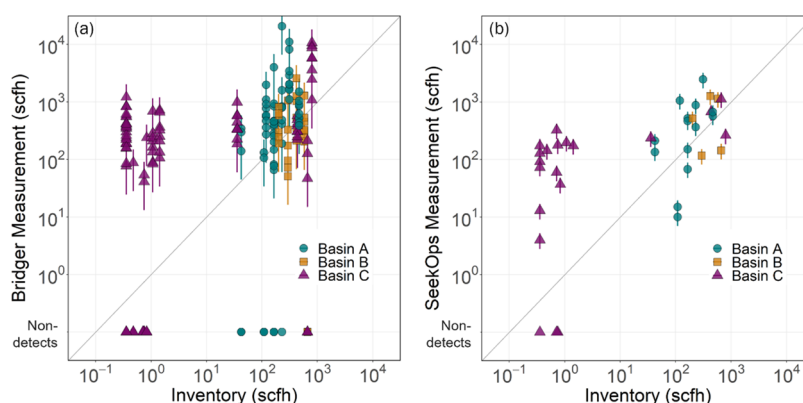
**Figure 1.** Parity chart of individual, aggregate, site-level emissions (*y*-axis) as measured by Bridger Photonics (a) and SeekOps (b) in comparison with GHGRP-based inventory estimates (*x*-axis) for each of the sites in basins A (turquoise circles), B (yellow squares), and C (purple triangles). 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.[11,44]

enrolled assets when weather conditions allowed. Operators are aware of the measurement schedules of each measurement technology. The OGI team 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 nonenrolled assets operated by the producers participating in the QMRV project to assess whether 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. 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 component- and 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 to 24, 2021, from 5 facilities in basin B from July 26 to 28 and August 3, 2021, and from 25 facilities in basin C from August 23 to 26, 2021. Multiple surveys were conducted by each measurement technology, depending on the survey speed and time, and were designed to be contemporaneous to ensure comparability of the measured data. SeekOps, which typically takes 1−3 hours per facility, completed up to two surveys of each site. Bridger Photonics, being aerial technology, measured each site 6−11 times over 4−5 days across all basins. Several recent peer-reviewed studies describe the performance parameters of these technologies in detail.[10,44] Emissions attribution was done by direct data collection from technologies and cross-referencing with operator insight and field photos. The OGI team recorded the equipment associated with emitting components in their survey reports. SeekOps reported emissions by equipment group in basins A and B. In basin C, SeekOps was unable to measure at the equipment-level due to the operator's safety policy that sets flight distance restrictions for their drones. Therefore, SeekOps only provided site-level emission data. Bridger 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 source. Satellite observations were conducted at the 38 facilities. However, the instrument's sensitivity to cloud cover and aerosols in the atmosphere and surface features like water bodies resulted in few successful measurements. 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. Each site had 3−4 sensors depending on the size of the facility, the number of equipment with the potential to emit methane, and the 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) estimates. 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 Section S2).[45] SeekOps provided a summary report of measured emissions and wind-roses with detailed notes at each site. Measurements from all equipment in each facility were aggregated to calculate the total facility-level emission rate. A high-resolution field photo was also provided for each facility. Bridger conducted 2−3 rounds of measurements per day for each facility including multiple passes over the same facility during each round of measurement and provided a detailed breakdown of measured emissions from each pass by emission location. 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 (see Section S4).

In addition to measurements, each operator was also required to submit conventional emission inventory reports, estimated through EPA's GHG Reporting Program (GHGRP) methods for individual sources.[46] Emissions that are known to be excluded in the GHGRP are also provided as the Supporting Information to allow the comparison of measured emissions with inventory estimates (see 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 are not expected to bias this approach.

### 3.1. Inventory Estimates vs Measurements. 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 3 orders of magnitude—from less than 50 standard cubic feet per hour (scfh) to more than 10 000 scfh. This suggests 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 recently published studies.[22,23] For example, average site-level emissions, averaged across both measurement technologies, in basin A, basin B, and basin C are 1081, 473, and 373 scfh, respectively. By comparison, the average GHGRP-based inventory estimates in the three basins are 201, 432, and 97 scfh, respectively. Third, significant variations in site-level emissions imply that measured individual snapshot emissions can be lower or higher than inventory estimates, depending on the time of measurement. In basin A, two out of eight 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 three out of eighteen sites in basin C are consistently at least 1 order of magnitude smaller than the 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 emission 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 intraday variations. 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 and 1062 scfh, with a GHGRP-based inventory estimate of 295 scfh.

### 3.2. Equipment-Level Temporal Variations in Emissions. Site-level temporal variations in emissions can be attributed, in part, to specific equipment groups. Figure 2
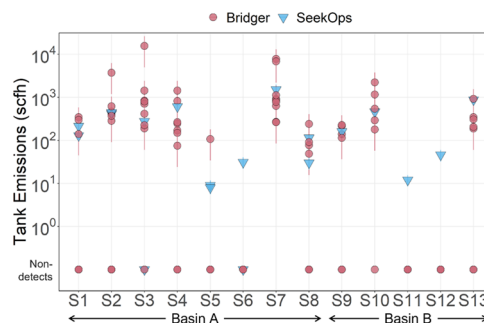


**Figure 2.** Aggregate tank-level methane emissions measurements by Bridger (red circles) and SeekOps (blue triangles) at all sites in basin A and basin B. Data points show both repeat measurements conducted on the same-day and multiday measurements at a site. Inventory estimates at these sites are between 40 and 700 scfh (see Figure 1).

shows the temporal variations 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.[37,39] Measurements in both basin A and B show that distribution of individual emission measurement from tanks span over 3 orders of magnitude—from as low as 10 scfh to over 10 000 scfh. Averaging emissions from each site across all measurements, we calculate average tank emission rates of 597 and 239 scfh in basin A and basin B, respectively. Thus, individual estimates of tank emissions can be multiple standard deviations away from the time-averaged emissions estimate, indicating that snapshot measurements will be insufficient to develop accurate annualized site-level 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 emission 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 level 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.

The variation in tank emissions shown in Figure 2 is tightly linked to total site-level emissions. Figure 3 shows the total site-level emissions in basin A and B, disaggregated by three major equipment types typically seen at upstream production facilities—tanks, gas processing units (GPUs), 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 colocated equipment. We make a few important observations. First, emissions vary by about an order of magnitude across basins, with basin A exhibiting significantly higher emissions associated with tanks
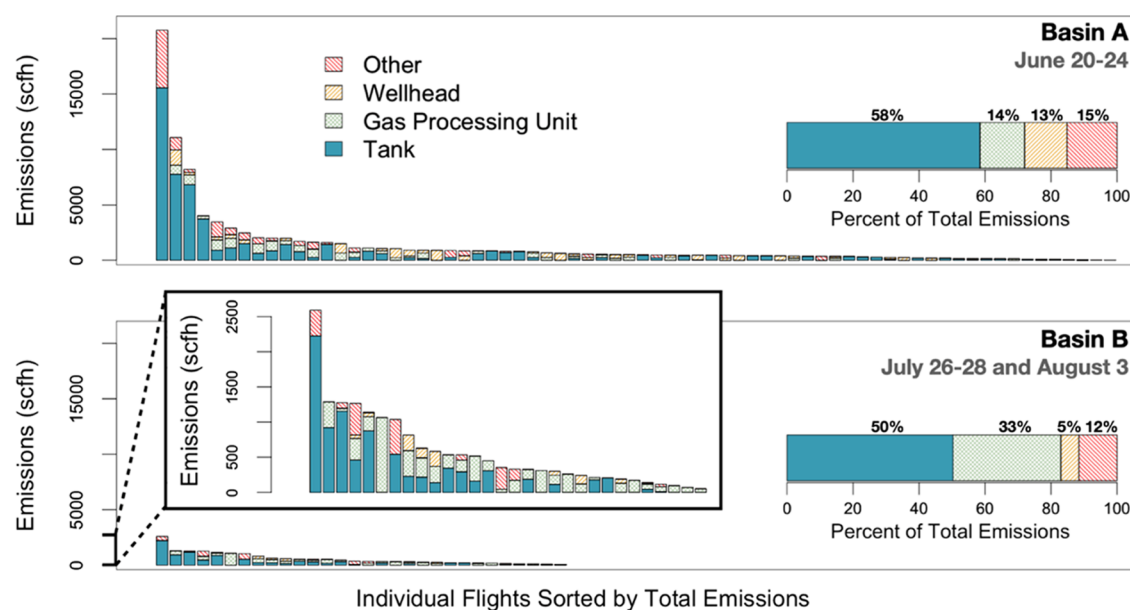
**Figure 3.** Site-level emissions in basin A (top) and basin B (bottom) disaggregated by three major equipment groups: tanks (turquoise), gas processing units (pale green), wellheads (beige), and other equipment on site (pink). Each bar represents a single round of measurement by either Bridger or SeekOps 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%).

compared to basin B. Second, tank emissions dominate total emissions in both basins, contributing 58% and 50% of total emissions 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 nondominant 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.

**3.3. Intraday Temporal Variations.** Intraday variations 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 failures such as broken level indicators and thief hatches. Figure 4 shows the time series of the 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 the detection threshold and a high measurement of over 15 000 scfh. Bridger measured this high tank emission coming from four emission locations on three closely located tanks on site. Thus, the ability to identify short-duration but high-volume events is critical to developing accurate annualized emission inventories. Multipass measurements with aerial technologies reveal the importance of characterizing intraday emission variations. Moreover, while emission attribution of measurements from aerial technologies is an ongoing field of research, comparing operational data with snapshot measurements can help with root-cause analysis. The key to explaining any discrepancy between measurements and emission inventory estimates requires an improved understanding of
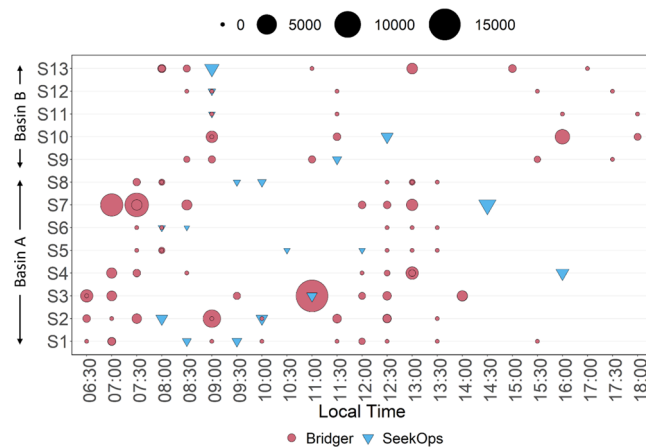


**Figure 4.** Time series of tank-related methane emissions observed on each site by Bridger Photonics (red circles) and SeekOps (blue triangles), where each row represents a site. The area of the dots represents the volume of emissions. All times are in local time of measurement.

the frequency and duration of emissions from variable sources such as tanks.

**3.4. Using Continuous Emissions Monitoring Systems (CEMS) to Estimate the 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 emission 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 a significant contribution from uncontrolled tank emissions (Figure 3, basin A) will be strongly correlated with the frequency and duration
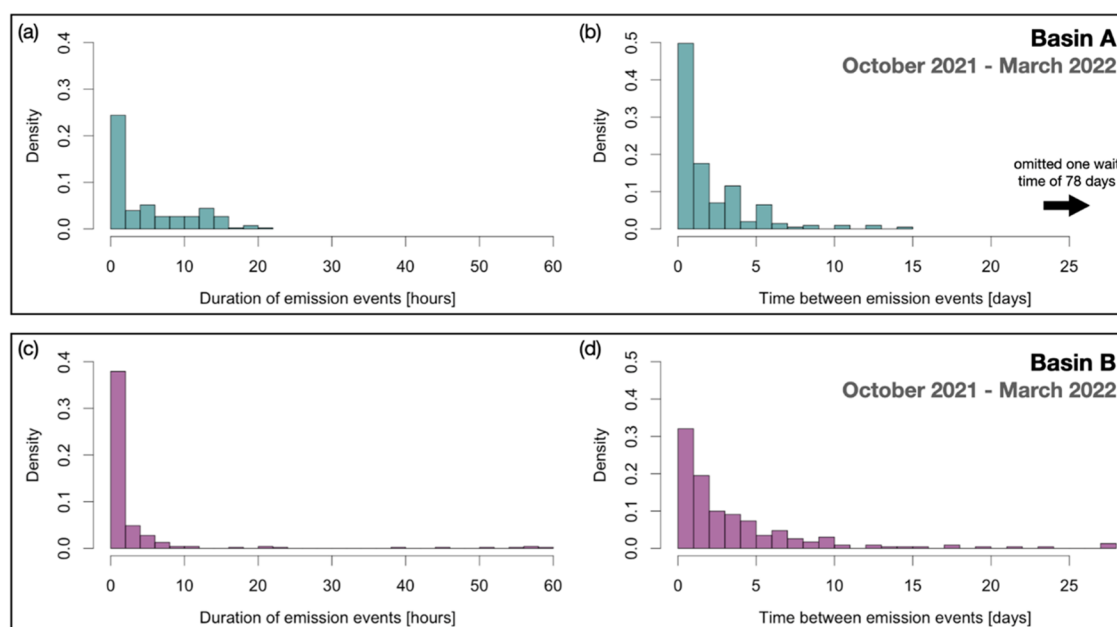
**Figure 5.** Empirical distributions of emission event durations (a, c) and wait times (b, d) between subsequent emission events recorded by CEMS in basin A (top panel, turquoise) and basin B (bottom panel, purple). CEMS data spans October 2021−March 2022. Note that a wait time of 78 days was omitted from (b) for visual clarity.

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 emission 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 Sections 2 and 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.[47−49] See Figure S13 for an example of emission events on an enrolled asset that were captured by the CEMS. Figures S2−S7 and S13 indicate that CEMS can detect small methane concentration enhancements on the order of 1 ppm. The CEMS used in this study were used during the 6 months of the enhanced monitoring phase as event detection sensors since quantification was not available. Because event detection relies on large changes in methane concentration, the analysis presented here is invariant to potential calibration errors or uncertainty in absolute concentration measurements. Future work will focus on emissions quantification using CEMS data.

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 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. As CEMS deployment expands, future work can explore these methods to develop facility and equipment-specific emissions statistics to scale snapshot measurements.

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 to 30 ppm were tested, and the conclusions we present here are consistent across thresholds (see Section S4.2 for details). We do not attempt a root-cause analysis for the events presented in Figure 5, as current CEMS solutions do not provide reliable localization capabilities. Therefore, a root-cause analysis at this stage would depend on records of site activity provided by the operator. Since record-keeping practices vary across operators, we believe that this would introduce unnecessary biases. Future work will use CEMS for

source localization. Also, no CEMS data were collected in basin C.

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 blowdown 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 (a) compared to that in (c) indicates that events (i.e., elevated methane concentrations) tend to last longer in basin A than basin B. Finally, (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 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.

## 4. DISCUSSION

Our multiscale field measurements described here find the following:

(1) Methane emissions in all three basins exhibit significant intraday and daily variations, resulting in a range of 3 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 level. However, individual sites can have significantly lower emissions than inventory estimates.

(3) Characterizing operator-specific distributions of the frequency and duration of intermittent emission 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 adjustments, 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 variations that impact emissions even within a basin or sub-basin.[16,50−52] In this context, multiscale measurements of methane emissions

have demonstrated the need for a robust approach to improve emissions inventories.

Based on the 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 CEMSs 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.[22,23] 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 and submissions to international collaborations such as the UNFCCC process. Given the importance of official inventories, it is important to leverage measurements to reconcile 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 variations in developing basin-level emissions estimates, such an approach is inadequate for developing target-based approaches to facility-level mitigation policies. Multiscale measurements at each facility that provide quantitative information on emission volume and frequency and duration of intermittent events are necessary to identify and update equipment-level or facility-level emission 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 update process-

based models such as the methane emission estimation tool (MEET) to better align with observations.[53,54] As technology—especially CEMS flux algorithms and emission 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 and providing robust uncertainty bounds on emissions based on operational and maintenance records, emission 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 the reported emissions estimates.[55] Statistical models can then be used to evaluate whether 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. It is important to have CEMS on a representative sample of the sites to be verified, which will change depending on the basin and operators involved. 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 multiscale 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, which will provide operational and climate benefits. While we recognize the challenges of going from zero to multiscale measurements, operators should consider developing monitoring plans that ramp up over a reasonable period. Technology developments in the last 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.

## ■ ASSOCIATED CONTENT

### ⓢ Supporting Information

The Supporting Information is available free of charge at https://pubs.acs.org/doi/10.1021/acs.est.2c06211.

> Additional details on the QMRV protocol, inventory estimations, and measurement technologies (PDF)
> Measurement data (XLSX)

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