Response to Request for Information on "Use of Advanced and Emerging Technologies for Quantification of Annual Facility Methane Emissions Under the Greenhouse Gas Reporting Program"

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1 Biographical Information

William Daniels, Philip Waggoner, and Dorit Hammerling are members of the Applied Mathematics and Statistics Department at the Colorado School of Mines. We have statistical expertise that allows us to bring a rigorous methodological understanding to the field of methane emissions monitoring. Furthermore, we bring additional expertise in mathematical modeling (e.g., dispersion modeling) through collaboration with the broader Applied Mathematics and Statistics Department at the Colorado School of Mines. The authors are members of the Energy Emissions Modeling and Data Lab, providing opportunities for close collaboration with other researchers working in the field of methane emissions monitoring.

We focus our response on continuous monitoring systems (CMS), as this measurement technology has been a specific focus of our research over the last three years. Furthermore, Dorit Hammerling has eight years of experience working with sensor data as input for automation purposes in challenging industrial environments. While we do comment on other measurement technologies within the context of our CMS discussion, this response is not intended to be an exhaustive discussion of these other technologies.

2 Response to Selected Questions

2.1 Quantification of Annual Emission Rates

a) **Detection and Quantification of Atmospheric Methane Emission Events from Advanced Measurement Technologies**

i. What advanced measurement technologies are currently available that can provide quantified methane emission rates using transparent, open-source, and standardized methodologies?

CMS are a broad class of measurement technology that take measurements of methane concentrations in near real time, typically at a frequency of one measurement per minute or higher. Like almost all other methane measurement technologies, additional analytical methods are required to translate these raw concentration measurements into more actionable information, such as leak detections or alerts, emission source location estimates, and emission rate or flux estimates.

CMS technologies fall broadly into four categories:

- *Point-in-space CMS.* Also referred to as point sensor networks, these CMS are comprised of multiple methane concentration sensors that are fixed in place, typically around the fenceline of an oil and gas site. The sensor network detects enhancements in the methane concentration data when wind blows emitted methane towards one of the fixed sensor locations.

- *Intrinsically safe CMS.* These CMS are comprised of sensors that can be installed directly on the potentially emitting equipment, rather than at the fenceline. This makes it easier to distinguish between potentially emitting sources, especially on complex sites.
- *Line integral CMS.* These CMS are comprised of a laser and multiple reflectors that the laser targets. The laser system is able to infer methane concentrations along the path of the laser between the laser source and the reflector. By placing the reflectors around an oil and gas site, the laser system can detect enhancements along lines transecting the site.
- *Camera-based CMS.* These CMS are similar to the line integral CMS, but instead of operating the laser along a single line between a source and a network of reflectors, the laser is directly targeted at equipment on the facility. Photons that reflect off of the equipment and return to the sensor are measured in a 2D grid. These photon counts plus a distance metric allow for a 3D calculation that provides a grid of inferred methane concentrations. Concentration enhancements from an emission source will appear as a methane plume in the concentration images.

What are the specific quantification approaches that have been used with these technologies, and how have these methodologies been demonstrated and validated?

Below we discuss the methodology used by each class of CMS to quantify methane emissions.

- *Point-in-space CMS.* Algorithms are required to translate the raw concentration data into emission rate estimates. The algorithms used by commercial solutions are not typically openly available, at least not in their entirety. Academic groups are developing and publishing methods for estimating emission rates [Cartwright et al., 2019, Kumar et al., 2022, Daniels et al., 2024a].
- *Intrinsically safe CMS.* Similar to point-in-space CMS, an algorithm is required to translate the raw concentration data from the sensors into emission rate estimates. The algorithms used by commercial solutions are not typically openly available, at least not in their entirety. Academic groups are developing and publishing methods for estimating emission rates [Cartwright et al., 2019, Kumar et al., 2022, Daniels et al., 2024a]. Unlike the point-in-space fenceline CMS, the intrinsically safe CMS are placed within the facility, potentially allowing for improved differentiation of emission sources in the inversion.
- *Line integral CMS.* Algorithms are required to translate the line integrals of methane concentrations into emission rate estimates. One commercial solution (Longpath) has published information about their emission rate estimation algorithm [Alden et al., 2018]. Academic groups are also developing and publishing methods for line integral CMS [Cartwright et al., 2019, Weidmann et al., 2022].
- *Camera-based CMS.* An algorithm is required to first identify the methane plumes in the 2D images of inferred methane concentrations, and another algorithm is required to then quantify the emission rate of the detected plumes. To the best of our knowledge, commercial solutions have not made their algorithms available. A large amount of literature exists for plume identification and quantification from concentration images, as this methodology is also required to quantify emissions using satellite data. For example, see [Jervis et al., 2021, Varon et al., 2018].

How can these technologies and quantification methodologies be used to provide annual data in a consistent manner for each future year of GHGRP reporting?

Emissions from oil and gas sites can come from many different pieces of equipment, each with their own unique emission characteristics. Emission rates can vary by orders of magnitude, and emission durations can be as short as seconds and as long as months (or indefinitely, until the leak is repaired through operator intervention). Importantly, emissions from many oil and gas equipment groups are highly temporally intermittent, meaning that they may go from no emissions to large emissions and then back to no emissions over short time scales.

When discussing annualized estimates of methane emissions ("annualized inventories"), the various emission sources can be aggregated at different levels. For instance, you can create an annualized inventory for a single piece of equipment, a site, or an entire basin. It is important to differentiate between these spatial scales, as the methods for addressing intermittency are often different for each.

We will quickly formalize this idea so that we can discuss annualized inventories more precisely. Let $\{X_1(t), ..., X_n(t)\}$ be the emission time series for n pieces of equipment. That is, at a given time t, equipment group i has emissions $X_i(t)$. If considering a single site, n may be on the order of 10 potential emission sources, but if considering a basin, n may be much larger, on the order of hundreds of thousands or millions. We have that

$$X_1(t) = \{X_1(1), X_1(2), ..., X_1(T)\}$$

$$X_2(t) = \{X_2(1), X_2(2), ..., X_2(T)\}$$

$$...$$

$$X_n(t) = \{X_n(1), X_n(2), ..., X_n(T)\}.$$

The annualized inventory for source i can be thought of as simply the average of that source's emissions over a year, which has some true value μ_i that we attempt to estimate through measurements. Call our estimate of the annualized average I_i, where the I stands for inventory, calculated as

$$I_i = \frac{X_i(t)}{T} = \frac{X_i(1) + X_i(2) + ... + X_i(T)}{T}.$$

Note that the year-long average rate is equivalent to the year-long total emitted mass, with the average just being equal to the total emitted mass scaled by the number of time steps within a year. When we estimate the annualized inventory using measurements, we desire our estimate to be unbiased, meaning that

$$\mathbb{E}(I_i) - \mu_i = 0,$$

where $\mathbb{E}(I_i)$ is the expected value of I_i. In other words, we want our estimate of the long-term average to be very close (ideally identical) to the true long term average. Importantly, this does not require each individual emission rate estimate at a given time to be perfectly accurate. In other words, our estimate of emissions at time t may be wrong, but when emissions at all time steps, $t = \{1, ..., T\}$, are averaged, then the resulting inventory, I_i, is accurate.

When considering aggregated emissions inventories, either at the site- or basin-level, we instead desire that $I = I_1 + I_2 + ... + I_n$ is unbiased, such that

$$\mathbb{E}(I) - \mu = 0,$$

where $\mu = \mu_1 + \mu_2 + ... + \mu_n$. That is, the sum of our estimated year-long average for each equipment group is equal to the sum of the true average emission rates for these equipment groups. As with the inventory for a single emission source, I_i, this unbiased property means that there is equivalence between I and μ in expectation, but there will be uncertainty, or variability, around this relationship. As such, for I to be close to μ, we need a large and representative sample of emissions both over time and over the set of potentially emitting sources of interest, e.g., from a facility or a basin.

When creating basin-scale inventories, it is often infeasible to measure each potential source many times. That is, it becomes infeasible to accurately estimate each I_i and instead an accurate estimate for just I is desired. In this setting, the issue of intermittency is overcome by measuring a large number of sites, either directly through aerial surveys (e.g., [Chen et al., 2022, Sherwin et al., 2024]) or in aggregate through inversions of satellite column retrievals [Shen et al., 2022]. This method of overcoming intermittency relies on the assumption that emissions from a given source are distributed according to a common distribution shared by many other sources, and therefore, by measuring many sites, a representative sample of emission states in their relative frequency will be observed [Tullos et al., 2021]. The assumption of a common emission distribution can be made at the basin-level, or at smaller scales (e.g., by operator or site type) [Johnson et al., 2023].

When creating site-level inventories, ideally only measurements of methane from a given site will be used to create the inventory for that site. Therefore, the issue of intermittency must be overcome by taking high frequency measurements at the site-level, as it is no longer possible to leverage data from multiple sites. High frequency measurements are necessary because large emissions can be short lived [Daniels et al., 2023] and hence may be missed by survey-based technologies. In an extreme example, assume that emissions from a given source, $X_i(t)$, are small for all times except $t = \tau$, at which the emissions suddenly jump to a much higher rate. The inventory for this source, I_i, will be underestimated unless the very large emission at time $t = \tau$ is included in the average. While this is an extreme example, emission rates do often follow a highly right-skewed distribution, meaning that the largest emissions are very rare [Brandt et al., 2016]. Survey-based measurement technologies, like airplanes or drones, might measure each site quarterly or monthly, which would only provide 4 or 12 measurements of each site per year, respectively. Given that large emissions occur infrequently and often don't last long, there is a high probability of missing large emissions that heavily influence the inventory for a given source when only using a small number of measurements.

CMS are currently the only measurement technology that are designed for this type of high-frequency, long-term measurement approach, making them particularly well suited for creating site-level emissions inventories. CMS can be used to create site-level inventories as follows. First, deploy the CMS sensors in an arrangement that provides optimal coverage [Jia et al., 2024]. This minimizes CMS "non-detect times," or the times when wind is not blowing emitted methane towards a point sensor (for point sensor networks), a laser path (for line integral methods), or into the view of the camera (for camera-based systems). Next run a quantification algorithm on the near real time concentration data collected by the CMS over the course of the year, such as the method proposed in [Daniels et al., 2024a]. After quantifying emissions, it is critical to still identify CMS non-detect times, as it is challenging to achieve 100% coverage of the site with a limited number of sensors, even under optimal placement. This can be done using the method in [Daniels et al., 2024b] or [Chen et al., 2023]. During non-detect times, it will appear as if no emissions are occurring, regardless of the true emission state, and as such, these times must be discarded when creating the inventory. Finally, the inventory can be created by simply averaging the emission rate estimates that occurred during the CMS detect times, or the times when the wind was blowing towards the sensors. The CMS non-detect times are solely a function of wind direction (i.e., detect times are when wind is blowing towards the sensors, and non-detect times are when the wind is blowing away from the sensors). Therefore, the emission rates during the non-detect times can be discarded, under the generally reasonable assumption that emission events on site are independent of wind direction. This means that the remaining emission rate estimates (i.e., those collected during the CMS detect times) will be an unbiased estimator of the long-term emission rate average. The resulting average value can be multiplied by the number of hours in a year to obtain an annual emissions estimate at the site-level that accounts for intermittency.

Are there specific detection and quantification approaches or methodologies that EPA should or should not consider?

At this point, there is not one clearly dominant inversion method for translating CMS concentration data into emission rate estimates. Any method that demonstrates adequate performance on controlled release experiments should be considered at this point (see discussion of question below). However, accounting for CMS non-detect times is critical for accurate long-term emission averages, and hence any method that does not identify these times should not be considered. We reiterate that the emission rates during these non-detect times can simply be discarded before computing the long-term average, as emission characteristics are generally independent of wind direction (see previous question for a full discussion of this point). Even after discarded the emission rates during non-detect times, CMS will still provide orders of magnitude more emission rate estimates than, e.g., quarterly aerial surveys, meaning that they will still be able to accurately estimate the long-term average at the site-level.

Furthermore, quantification approaches must be generalizable to many different facilities to be useful in practice. For example, a machine learning method, in theory, could be developed to accurately represent transport on a given site without the use of a physics-based dispersion model. However, it is unclear if that machine learning method would then be transferrable to a different site with a different configuration of emission sources and with different wind patterns. This can be assessed by testing the proposed methods on many different sites with different characteristics.

In terms of CMS measurement modalities, there is not one modality that is inherently better or worse than the others. Each has strengths and weaknesses. For camera-based sensors, they can be pointed directly at specific emission sources (e.g., compressor vents) to provide reliable detection of these known sources. However, they might not always provide full site coverage. For line integral-based sensors, they can potentially monitor many sites using a widely distributed array of reflectors around reflector tower, but they can be large and hard to install in tight areas or on hills. For point-in-space CMS, they can provide full site quantification, but might miss smaller emission sources in the presence of larger emissions.

ii. What performance metrics and threshold(s) related to quantification would be appropriate to apply to advanced measurement technologies for their incorporation into the GHGRP? For example, should EPA consider: thresholds for the methane detection limit (e.g., minimum emissions leak rate), thresholds for the probability of detection (e.g., rate of false positives or negative detections), specific levels of accuracy for quantification, specific measurement frequencies, or other?

We believe that the following performance metrics are the most important considerations when using CMS to create annualized, site-level inventories. In our discussion below, our use of the word "estimate" refers to emission rate estimates. CMS, along with almost all measurement technologies (besides flux chambers), must perform an inversion to estimate emission rates from what was directly measured (e.g., methane concentrations).

- *Low or no quantification bias.* Using the variables defined earlier, we desire an inventory I_i that is unbiased, that is $\mathbb{E}(I_i) - \mu_i = 0$. Bias in an emission rate estimate can be thought of as systematic error, or error that persists after averaging many estimates. Minimizing this type of error is critical for accurate CMS-based inventories, as these inventories will be constructed by averaging all CMS emission rate estimates within a given year (after discarding estimates during non-detect times - see earlier discussion). Methods like [Daniels et al., 2024a] have minimal quantification bias based on controlled release experiments.
- *Minimum detection limit.* This is important for annual inventories, as missed emissions below a given threshold will bias the resulting inventory estimate low. This can be partially corrected for by supplementing measurements with factor-based inventories for known emissions below the detection limit (see e.g., [Johnson et al., 2023]). CMS-based technologies tend to have very low minimum detection limits (e.g., the [Daniels et al., 2024a] algorithm has a detection limit < 0.5 kg/hr and commercial solutions are starting to show similar detection limits [Cheptonui et al., 2024]).

We also note that sampling frequency is a key consideration for constructing site-level emissions inventories. CMS solutions all typically have high sampling frequencies by design. Quarterly aerial surveys of a given site, for example, are typically not a sufficiently large sample to accurately scale to an annual site-level inventory (more discussion of extrapolation below). Conversely, it would be challenging to install CMS on a large enough sample of sites to provide a representative spatial sample to estimate a basin-level inventory, whereas survey-based technologies can quickly measure many sites. Furthermore, survey-based measurements are a very useful tool for calibrating CMS-based emission rate estimates on a given site and for identifying emission sources on the site.

What would be a feasible approach for developing these thresholds and metrics?

Controlled releases provide the most direct way of evaluating these performance evaluations and metrics. It is important for these controlled release evaluations to first start simple (e.g., distinct emission events with no background emissions) and progressively get more realistic (e.g., multiple emission sources simultaneously emitting with overlapping start and end times and background emissions). Advancing the sensors and quantification algorithms underpinning the various methane measurement technologies is a challenging task, but is progressing rapidly. It therefore makes sense to perform iterative evaluations, where each new iteration of the evaluation tests a new feature of the technology.

For example, for point-in-space and line integral CMS, it is much easier to estimate emission rates without background emissions from, e.g., many pneumatic devices, but instead only a small number of larger equipment groups that are emitting, like tanks and compressors. It therefore makes sense to first ensure that CMS quantification algorithms can accurately estimate emission rates in the "clean" setting without background emissions, and once this is established, add in background emissions. This allows for disentangling sources of quantification error.

In the longer run, it is also important to evaluate CMS under many different conditions and in different settings. Therefore, ideally, there would be multiple different controlled release facilities available for testing CMS (as well as other measurement technologies). This would avoid unintentionally designing CMS to work well at one given controlled release facility without generalizing well to other facilities. Furthermore, evaluating CMS at operating facilities is an important tool to assess their performance in real-world conditions. Evaluations at operating facilities can be conducted using controlled releases of methane in addition to emissions from normal operating conditions on the site [Day et al., 2024, Yang and Ravikumar, 2024]. Additionally, evaluations can be conducted at operating facilities without any controlled releases by assessing the degree of alignment between different CMS solutions (see [Daniels et al., 2024c] for an example).

b) **Extrapolating Quantified Methane Emission Rates to Calculate Annual Emissions for GHGRP Reporting Purposes**

i. What advanced measurement technologies are currently available that can provide annual total methane emission estimates for specific regions, facilities, processes, or equipment-level sources, that use transparent, open-source, and standardized methods?

There are many different methane measurement technologies beyond CMS, such as aerial survey-based technologies and satellites, that can provide methane emission estimates at larger spatial scales. However, CMS are particularly well suited for creating annual total methane estimates at the site- and equipment-level, as their high sampling frequency accounts for intermittent emissions (see discussion above). Creating a region-level inventory using only CMS would require installing CMS on all sites in the region, or installing CMS on a subset of the region and extrapolating to the remaining sites. Ideally, multiple methane measurement technologies would be deployed simultaneously, allowing for more information from different types of measurements.

Are there specific annual extrapolation approaches or methodologies that EPA should or should not consider?

We believe that using a limited number of survey-based measurements (e.g., quarterly aerial surveys) does not provide a large enough sample to accurately extrapolate to a site-level annualized inventory. See earlier question for a discussion of how CMS data can be used to create annualized, site-level inventories.

2.2 Attribution

a) **What methodologies are currently available that can attribute quantified methane emission events to specific equipment types (or additionally, specific regions, facilities, or processes) using transparent, open-source, and standardized methods? Are there specific attribution approaches or methodologies that EPA should or should not consider?**

Many inversion technique used to translate CMS concentration observations into emission information can attribute emission to specific emission sources. These methods typically fall into two categories: 1) methods that pre-specify potential emission sources before running the inversion [Daniels et al., 2024a, Alden et al., 2018], and 2) methods that estimate emission rates on a grid overlaying the site, where "hot spots" indicate an emitting piece of equipment [Hirst et al., 2020, Weidmann et al., 2022].

b) **What accuracy or uncertainty metrics would be appropriate for GHGRP reporting purposes? For example, what level of confidence in the source attribution would be necessary for advanced measurement technologies to meet for GHGRP reporting purposes? What would be a feasible approach for developing these thresholds?**

The level of acceptable attribution uncertainty depends on the intended use-case of the localization estimate. For equipment-level, annualized inventories, the most important accuracy metric is the long-term average emission rate at the equipment-level. Emission rate estimates at the equipment-level have uncertainty in both their rate and source attribution. For example, a given emission from a separator may be quantified accuracy (i.e., the rate is correct), but it may be incorrectly attributed to the tanks rather than the separator. If there is bias in this type of error (i.e., if more separator emissions are incorrectly attributed to the tanks than tank emissions are incorrectly attributed to the separators), then the equipment-level inventories will be incorrect. As such, the important performance metric is the long-term average of the emission rate estimates at the equipment-level. This metric can be assessed at controlled release facilities, like METEC, that can perform releases for multiple pieces of equipment (ideally at the same time).

For an alerting use-case, the variability of the attribution estimate matters, as an individual emission estimate that is incorrectly attributed may result in mitigation teams being sent to the wrong source with the wrong equipment to address the actual emission. To assess this type of error, the following metric could be accessed using controlled release experiments. For a controlled release facility with five potential emission sources, for what percent of releases did the inversion technique correctly identify the emission state of all five sources (i.e., as either emitting or not emitting), what percent of releases did the inversion technique correctly identify the emission state of four sources, etc. Additionally, the average number of correctly identified emission states per release could be calculated across controlled releases.

c) **To what extent would standards and protocols need to be specific to the type of methods and ancillary data used (e.g., infrastructure datasets) or the type of emission source sampled (e.g., large unintended vs small routine emissions event)?**

CMS should be used differently at simple production facilities versus complicated midstream facilities. At complex midstream facilities, such as large compressor stations, it is more challenging to correctly identify a specific source as emitting or not emitting. This is because the sensors often have to be placed farther from the sources, and the sources are closer together than production sites with distinct equipment groups like wellheads and separators. At midstream facilities, CMS may need to be deployed such that separate sectors of the facility are treated independently and then summed, rather than attempting to provide full coverage of the entire site with the same set of sensors. Ideally, multiple different types of CMS would be deployed on these complex facilities. For example, intrinsically safe CMS could be installed on nearby equipment groups to help differentiate between their emissions, camera-based CMS could be pointed at hard to reach but known emission sources, and point-in-space CMS could be installed on the fenceline to capture emissions not targeted by the other technologies. Note that in this example, the point-in-space fenceline sensors could leverage the emission localization information provided by intrinsically safe sensors and camera-based systems.

2.3 Implementation

a) **Structure of Approaches or Protocols**

i. What form would standard method(s) or protocol(s) need to take to ensure that advanced measurement technologies provide annual total, source-specific, methane emissions in a transparent and standardized way?

Methane measurements in practice are often conducted by private companies, whose inversion methodologies are not always publicly available. While these solutions can be evaluated via controlled releases, their underlying methodologies may remain proprietary. As such, we believe that open-source methods being produced in academic settings can be used to benchmark the often proprietary, private solutions. In other words, open-source tools could be used as a starting point for proprietary solutions, which would ensure a minimum level of accuracy across the private solutions being implemented in practice. Private solutions could then extend the open-source tools using their own methods that would be evaluated via controlled releases. For example, [Daniels et al., 2024a] could be used to benchmark localization and quantification estimates from CMS, and [Daniels et al., 2024b] could be used to benchmark duration estimates from CMS.

3 Summary of Key Findings

Finding #1: CMS are particularly well suited for site-level annual inventories, as their high frequency measurements require no (or minimal) temporal extrapolation. For creating annual inventories, low (or ideally no) bias in the long-term average emission rate is the most important CMS performance metric. High variability in individual emission rate estimates is an important factor to consider for individual emission alerts, but this variability will get "averaged out" when computing a long-term emission estimate and is less of a problem when many individual estimates are averaged.

- **Recommendation:** When deciding if specific CMS solutions can be used for estimating annual emissions at the site-level, prioritize solutions with low error in their long-term emission rate estimate, or equivalently in their cumulative emissions estimate. Furthermore, CMS solutions must be generalizable to different conditions and facilities, especially if they use machine learning methods rather than physics-based dispersion models.

Finding #2: CMS can complement survey-based measurement technologies by bounding the duration of detected emissions. When using CMS to estimate durations, one must account for CMS "non-detect times," or the times when emitted methane is not blown towards a CMS sensor. This point is discussed in detail in other responses to this RFI, and as such, we discuss it only briefly here.

- **Recommendation:** Allow the use of CMS for bounding emission durations, but make sure that CMS solutions are addressing the issue of "non-detect times."

Finding #3: Inversion techniques to translate raw CMS concentration measurements into emission rate estimates are improving rapidly, both in the private sector and in academic settings. Open-source academic solutions can be used to benchmark private solutions and provide a minimum level of performance, as private solutions can always adopt the available open-source tools.

- **Recommendation:** EPA should continue to support the improvement of open-source modeling frameworks for continuous monitoring systems and establish a pathway to approve open-source models for use in regulatory applications.

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