Estimating methane emission durations using continuous monitoring systems

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Abstract

A small number of large emissions contribute a significant portion of total emitted methane from the oil and gas sector, making them a critical pathway toward emission reduction. These large emissions are often detected by snapshot measurements from aerial or satellite platforms, which have limited ability to characterize emission duration due to the relatively low frequency at which they observe a given source. Duration estimates are necessary for computing the total methane emitted by a given release and will be required for all emissions >100 kg/hr under proposed updates to the EPA's Greenhouse Gas Reporting Program (GHGRP). Continuous monitoring systems (CMS) are a monitoring technology that measure methane concentrations in near-real time and hence can complement snapshot measurements by bounding the duration of detected emissions. However, CMS will not record concentration enhancements during an emission if wind blows emitted methane away from the sensors. We propose a method for estimating emission durations using CMS that accounts for these non-detect times. The method has an average error of 6.3% when evaluated on controlled releases, with 88.5%

of estimates within a factor of 2x error from the true duration (i.e., percent error within [-50%, 100%]). We apply the method to a typical production site in the Appalachian Basin and use it to bound the duration of snapshot measurements. We find that failing to account for CMS non-detect times on this site results in underestimated emission durations of up to a factor of 71x (7,000%).

Keywords: methane, oil and gas, emission duration, emission frequency, continuous monitoring systems, greenhouse gas reporting

Synopsis: We develop a method to estimate methane emission durations and use it to bound the duration of snapshot measurements.

Introduction

Proposed updates to the EPA's Greenhouse Gas Reporting Program (GHGRP) will require oil and gas operators to report maintenance or abnormal methane emissions greater than 100 kg/hr starting in 2025,[1] including emissions identified by third parties (e.g., Carbon Mapper[2]). With an increasing number of operators opting into voluntary aerial measurement campaigns and with new methane-focused satellites (e.g., MethaneSAT[3]) coming online in the near future, the number of detected emissions meeting this reporting requirement is likely to increase.

A duration estimate is required for all emissions exceeding the 100 kg/hr reporting threshold so that a total mass of methane can be computed and reported under the proposed rule.[1] Infrequent snapshot measurements have limited ability to characterize emission duration due to the relatively low frequency at which they observe a given source. For example, an aerial measurement campaign measuring each site quarterly will only be able to bound emission start times at three month intervals, despite emissions potentially lasting for only a few hours or days.[4] Satellites can provide more frequent measurements of a given source, but their current detection limits are greater than the 100 kg/hr threshold in practice and cloud cover and surface albedo can also prevent detections.[5]

Higgins et al.[6] propose methods for bounding emission durations using operational data, such as tank pressures from a Supervisory Control and Data Acquisition (SCADA) system. They note that these methods will be useful to oil and gas operators for near-term regulatory compliance as measurement-based methods for estimating emission durations evolve, such as more frequent aerial sampling[7,8] or supplementing snapshot measurements with continuous monitoring systems (CMS).[9]

In this work, we develop improved methods for estimating methane emission durations using point-in-space CMS. These sensor systems measure methane concentrations in near-real time at several fixed sensor locations, typically around the perimeter of oil and gas sites. In practice, 1 to 10 CMS sensors may be installed on a given site, depending on its complexity and the CMS technology vendor.

There are often times when emitted methane is not blown toward any of the CMS sensors on a given site, which we will subsequently call "non-detect times." During these times, the sensors will not record enhanced methane concentrations, making it naively appear as if no emissions were occurring. In a simulated one-source scenario, Chen et al.[10] find that non-detect times make up 78% of total time when using one CMS sensor and 45% of total time when using four CMS sensors with a 0.2 ppm detection threshold.

Because of CMS non-detect times, there is often a delay between emission onset and detection that varies according to the number of deployed sensors, their sensitivity, and the meteorological conditions. In a case study, Chen et al.[11] find that the time to detection on a typical tank battery was 12 hours on average when using one CMS sensor and 4.3 hours on average when using four CMS sensors. However, they note that these CMS detection times are much shorter than, e.g., quarterly sampling.

Here we propose the first method for directly estimating methane emission durations using CMS that accounts for non-detect times when the wind does not blow emitted methane toward the sensors. We find that ignoring non-detect times can result in dramatically underestimated durations, especially when a small number of CMS sensors are installed on a given site (providing limited coverage) as is often done in practice.

We apply the proposed method to CMS data collected at the Methane Emissions Technology Evaluation Center (METEC) during non-blinded, single-source controlled releases to demonstrate its practical feasibility. We then apply the method to CMS data collected on an oil and gas production site in the Appalachian basin as a part of the Appalachian Methane Initiative (AMI) and use it to bound the duration of snapshot aerial measurements.

Methods

We create duration estimates by first clustering concentration enhancements into "naive" events that do not account for CMS non-detect times. For each naive event, we then determine when the wind is blowing toward or away from the CMS sensors, which we call periods of "information" or "no information," respectively. If two naive events with the same emission source are separated by a period of no information, we then compute a probability of combining the two events based on their estimated emission rate. Finally, we sample from the possible start and end times for each naive event, taking into account the information mask and the probability of combining events. This sampling creates a distribution of possible emission durations for each naive event.

We summarize this methodology in Figure 1 and discuss it in more detail in the following subsections. For reference, Figure S1 in the Supporting Information (SI) file shows a typical oil and gas production site with point-in-space CMS sensors arranged around the perimeter.

Identify naive events. We use the clustering procedure from Daniels et al.[12] to identify the naive emission events. Specifically, we start by taking the minute-by-minute maximum across the concentration data from all CMS sensors installed on the site. This collapses the signal from each sensor into one time series while preserving the concentration enhancements that contain emission information.

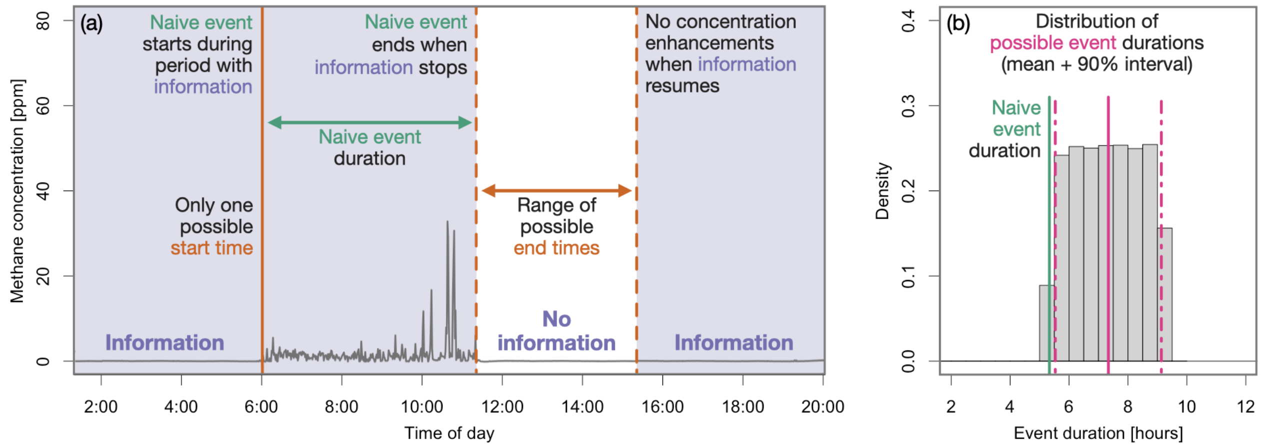

Figure 1: High-level summary of the proposed method for creating duration estimates that accounts for CMS non-detect times. (a) Concentration data corresponding to an example emission event. Naive duration is marked with a turquoise arrow. Periods of information are shaded in purple. Possible start and end times are indicated in orange. (b) Distribution of possible durations for the event in (a).

We then apply the spike detection algorithm from Daniels et al.[12] to this maximum value time series, which uses a gradient-based method to identify sharply elevated concentration values, or spikes. We cluster all identified spikes into groups and background correct them by subtracting the average of the concentration values immediately preceding and following the group. All concentration values not in a group are deemed background and are set to zero. The clusters of background-corrected enhancements are taken as the naive events.

Finally, we estimate the emission source for each naive event, which allows us to create a more accurate information mask. This step imposes the assumption that each naive event has a single source. We create source estimates using the method from Daniels et al.[12], in which forward simulations from each possible source are compared to the CMS concentration observations. The source whose simulated concentrations most closely match the actual concentration observations (assessed using correlation) is selected as the source estimate for that particular naive event. We use the Gaussian puff atmospheric dispersion model to forward simulate.[13]

Create information mask. Next we identify periods during which we expect the wind to blow methane toward the sensors (periods of "information") and between the sensors (periods of "no information"). We do so for each naive event by first simulating methane concentrations at the CMS sensor locations assuming an emission is occurring at the estimated source for that event. We do this using the Gaussian puff atmospheric dispersion model and the actual wind data collected on the site. Similar to the procedure for identifying naive events, we then take the minute-by-minute maximum of the simulated concentrations across all sensors on the site and apply the spike detection algorithm from Daniels et al.[12] to this maximum value time series. Clusters of identified spikes in the simulated concentrations are taken to be periods of information, as these are the times during which a simulated emission event created concentration enhancements at the sensor locations.

Compute probability of combining naive events. Occasionally, two naive events with the same source estimate are separated by a period of no information. There are two possible emission scenarios that could give rise to this situation: 1) the emission continued through the period of no information, and 2) the emission stopped and started again during the period of no information. We make the assumption that two naive events separated in this manner are more likely to be from the same emission if their estimated rates are similar.

We define the probability of combining a given naive event, E_i, with a neighboring event, E_j, as

$$\mathbb{P}_{i,j} = 1 - \frac{|q_i - q_j|}{\max(\boldsymbol{q}) - \min(\boldsymbol{q})}, \tag{1}$$

where q_i and q_j are the estimated emission rates of naive events E_i and E_j, respectively, and $\boldsymbol{q}$ is a vector of estimated emission rates for all naive events. If it is not possible to produce a rate estimate for E_i or E_j, then we set $\mathbb{P}_{i,j} = 0.5$, which assigns equal probability of combining and not combining the two events. A rate estimate is not produced when we determine that the Gaussian puff atmospheric dispersion model is poorly representing actual transport during a given event (see Daniels et al.[12] for details). If E_j has a different source estimate than E_i or is separated by a period of information, then we set $\mathbb{P}_{i,j} = 0$.

We estimate emission rates using the procedure from Daniels et al.[12], which minimizes mean square error between simulated concentrations and concentration observations from the CMS sensors over a range of possible emission rates. The emission rate that minimizes this error is selected as the rate estimate for the given event. Note that estimating emission frequency is straightforward once $\mathbb{P}_{i,j}$ has been computed for each pair of naive events. See Section S2 in the SI for details.

Create distribution of possible durations. We first identify all possible emission start and end times for each naive event using the logic displayed in Figure 1. If a naive event starts or ends during a period of information, we assume that there is only one possible start or end time for that event. However, if a naive event starts at a transition from a period of no information to a period of information, then any time up to the last period of information is taken as a possible start time. Similarly, if a naive event ends at a transition from a period of information to a period of no information, then any time up to the next period of information is taken as a possible end time.

For a given naive event, E_i, we then sample 10,000 times from its possible start and end times to create a distribution of possible durations. If a neighboring naive event, E_j, has a non-zero probability of being combined with E_i, then we sample start times (if E_j comes before E_i) or end times (if E_j comes after E_i) with probability $\mathbb{P}_{i,j}$ from E_j and with probability $1 - \mathbb{P}_{i,j}$ from E_i. This procedure creates a distribution of durations for each naive event, and a point estimate can be produced by taking, e.g., the mean or maximum (if an upper bound on the possible durations is desired).

It is possible for a given naive event, E_i, to be combined with more than just the two immediately neighboring events. If more than one event, either preceding or following E_i, have non-zero probability of being combined with E_i, then the procedure for sampling start and

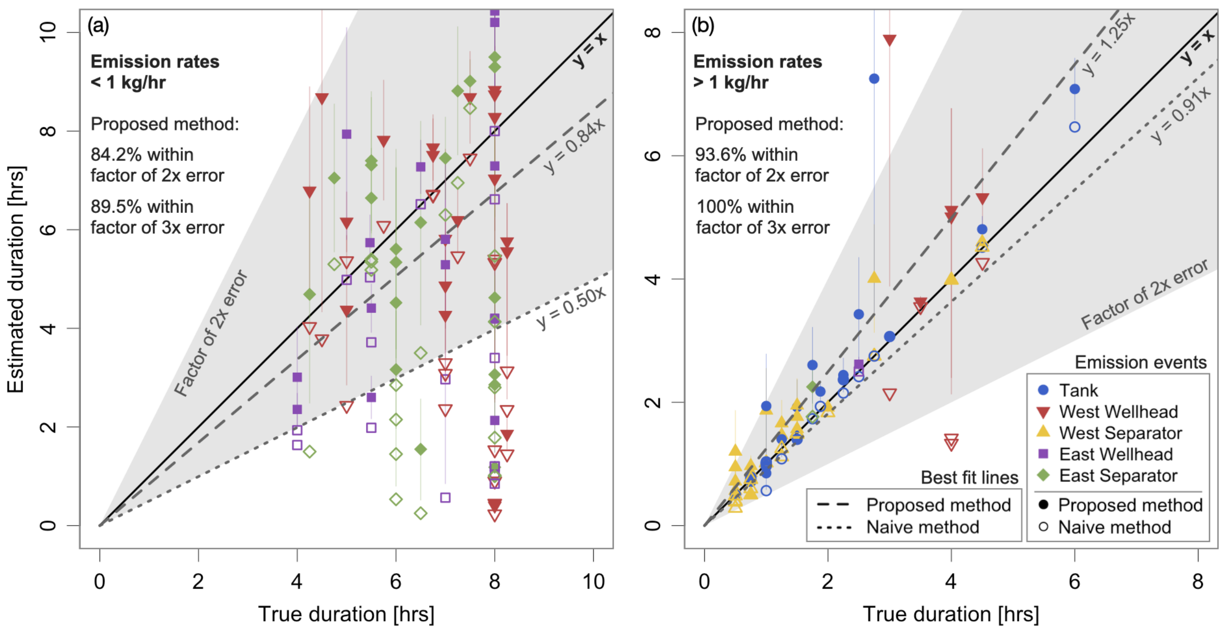

Figure 2: Results of non-blinded controlled release testing using 8 CMS sensors, separated by true emission rates <1 kg/hr (a) and >1 kg/hr (b). Solid and empty points correspond to duration estimates from the proposed and naive methods, respectively, with vertical lines showing the 90% interval from the proposed method and color showing the true emission source. Dashed and dotted lines show the best linear fit to the proposed and naive methods, respectively. Estimates within the gray shaded region are within a factor of 2x error from the true duration (i.e., percent error within [-50%, 100%]).

end times described above is applied recursively until an event with $\mathbb{P}_{i,j} = 0$ is encountered.

Results

We evaluate the proposed method on non-blinded, single-source controlled releases conducted at METEC as part of the Advancing Development of Emissions Detection (ADED) research program.[14] Non-blinded data are used for this preliminary evaluation because blinded data were not available when developing the proposed method, and hence further blinded testing is needed to more rigorously assess the method's performance. We use the non-blinded data solely for evaluation, as the duration estimates in this section were generated from estimated emission sources and rates rather than the true values provided by METEC.

Methane concentration data for this evaluation came from 8 CMS sensors placed around the perimeter of the METEC facility. Section S1 in the SI contains the full sensor specifications and shows the arrangement of sources and sensors during this experiment.

Note that the ADED experiment was conducted such that all of the short duration releases had large emission rates and all of the long duration releases had small emission rates. Additionally, the emission rates in this experiment (0.18 to 6.39 kg/hr) are relatively small compared to the 100 kg/hr threshold in the proposed EPA rule. Since smaller emissions are generally harder to detect, the performance of the proposed method on 100 kg/hr or larger emissions will likely be better than what is shown here.

Figure 2 compares duration estimates from the naive and proposed methods to the true controlled release durations. Both methods have a tendency to underestimate durations during the longer, lower-rate releases (Figure 2(a)), as long releases present more opportunities for non-detect times to separate concentration enhancements into shorter naive events. The proposed method is able to probabilistically recombine these short events and hence is less likely to underestimate in this regime.

Duration estimates for the shorter, higher-rate releases (Figure 2(b)) are more accurate, with 93.6% of estimates from the proposed method falling within a factor of 2x from the true duration. In this regime, the naive and proposed methods have similar performance, which is likely a result of two considerations. First, the higher-rate releases have shorter duration, meaning that there are fewer opportunities for non-detect times to separate concentration enhancements into shorter naive events that need to be probabilistically recombined. Second, the 8 CMS sensors used in this experiment provide good coverage of the potential emission sources, meaning that there are relatively few non-detect times and hence the proposed method does not notably alter many of the naive duration estimates.

The naive method is more prone to underestimation when fewer CMS sensors are used. To demonstrate this behavior, we omit data from half of the sensors and recompute the duration estimates from both the naive and proposed methods. These estimates are shown

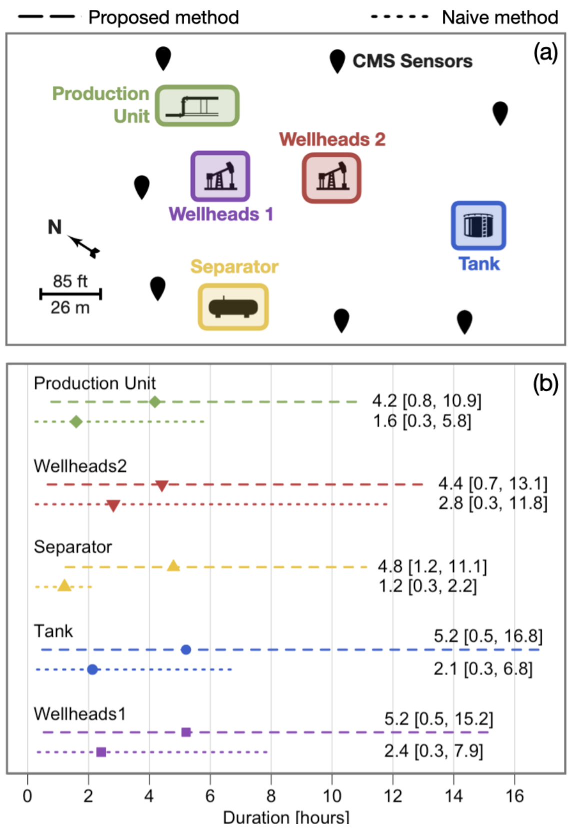

Figure 3: (a) Schematic of the oil and gas production site used as a case study in this article. (b) Range of duration estimates across all emission events from the proposed duration model (dashed lines) and the naive method that does not account for CMS non-detect times (dotted lines). Duration estimates from the proposed method are taken as the mean of all possible durations. The left- and right-most points of the horizontal lines show the 5^{th} and 95^{th} percentiles of the duration estimates, respectively, and the symbols show the mean. These values are also printed on the figure in the format: mean [5^{th} percentile, 95^{th} percentile].

in Section S3 in the SI using the same parity plot structure. The slope of the best fit line for the proposed method is relatively unchanged when moving from 8 to 4 sensors, dropping from 0.84 to 0.82 for lower-rate releases and from 1.25 to 1.23 for higher-rate releases. The slope of the best fit line for the naive method, however, drops notably with fewer sensors, changing from 0.50 to 0.34 for lower-rate releases and from 0.91 to 0.53 for higher-rate releases. This occurs because there are more opportunities for wind to blow emitted methane between the sensors when they are spaced farther apart, making it crucial to account for CMS non-detect times.

We now apply the proposed method to CMS data collected on an oil and gas production

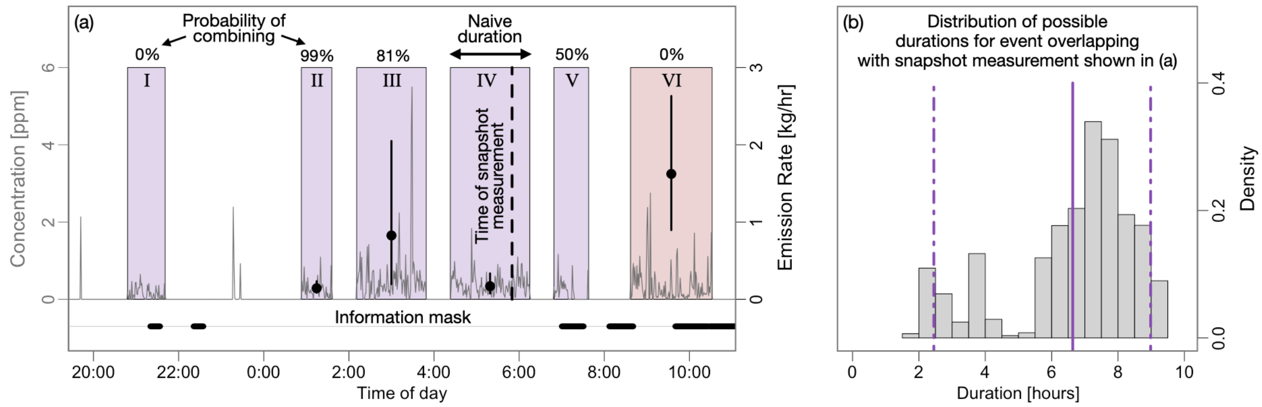

Figure 4: (a) Example snapshot measurement (vertical dashed line) and the overlapping CMS concentration data. Shaded regions show naive events, with color indicating the source estimate (see Figure 3) and black circles indicating the rate estimate. Thick black lines beneath the events indicate periods of information. Percents indicate the probability of combining each event with naive event IV. (b) Distribution of possible durations for naive event IV and the overlapping snapshot measurement, with vertical lines showing the mean and 90% interval.

site as a part of the Appalachian Methane Initiative (AMI). Figure 3(a) shows a schematic of the site with potential emission sources and CMS sensor locations marked. No production sites enrolled in the AMI project with CMS sensors had a snapshot measurement over 100 kg/hr. Therefore, this site was selected for illustrations because it was the simplest site with CMS and hence was most likely to satisfy the single-source assumption imposed by the duration model.

Figure 3(b) shows the range of estimated durations from both the naive and proposed methods across all identified emission events on the site shown in Figure 3(a). As with the METEC experiment, the naive method underestimates durations compared to the proposed method. Section S2 in the SI lists the emission frequency estimates for this site.

We now use the proposed method to bound the duration of an example snapshot measurement on the site shown in Figure 3(a). Because there were no snapshot measurements greater than 100 kg/hr on this site, we select a time for the measurement that best illustrates the proposed duration model, despite no actual snapshot measurement occurring at this time. Figure 4 shows the time of this example measurement and the overlapping CMS data. Note that CMS concentration enhancements are possible during periods of no information (e.g., naive events II, III, and IV) because the Gaussian puff model used to identify these periods is an imperfect representation of actual atmospheric dispersion. Therefore, periods of information are subject to dispersion model-induced errors.

Without accounting for non-detect times, one might use the duration of naive event IV as the duration estimate for the overlapping snapshot measurement. However, there are multiple naive events also localized to Wellheads 1 surrounding event IV, many of which are separated by periods of no information. Taking this into account via the proposed duration model results in a wide distribution of possible emission durations for event IV (shown in Figure 4(b)), and hence a wide distribution of possible durations for the overlapping snapshot measurement. Specifically, the naive duration estimate (1.9 hrs) underestimates the mean (6.6 hrs) and maximum (9.5 hrs) duration estimates from the proposed method by a factor of 3.5x and 5.0x, respectively. This underestimation would impact the estimate of total emitted methane to the same degree.

Finally, to probe the extent of possible underestimation by the naive method, we repeat our analysis on this site for all possible snapshot measurement times. The largest instance of underestimation was by a factor of 35.7x and 70.6x compared to the mean and maximum, respectively, of the duration distribution from the proposed method. More details about this case study, including duration estimates for two additional snapshot measurement examples, are given in Sections S4-S6 of the SI file.

Discussion

This study has revealed a number of necessary considerations for aerial measurement campaigns and the proposed EPA rule coming into effect in January 2025:

1. CMS can compliment snapshot measurements by bounding the duration of detected emissions. Aerial measurements alone have limited ability to bound durations, as

measurement campaigns are often performed only quarterly or yearly. Operational data can also be used to estimate durations, but these estimates will not be derived from direct measurements of methane.

2. If ignored, CMS non-detect times can result in significant underestimation of emission duration, to the point where the use of CMS could unintentionally circumvent a majority of the methane fees associated with large emissions. As such, probabilistically addressing CMS non-detect times is critical for accurate duration estimates.

3. We propose a method for estimating emission durations using CMS that probabilistically accounts for non-detect times. The benefit of this method is especially apparent when a small number of sensors (e.g., 4) are installed on a given site, which is common in practice, as this results in limited coverage.

Current commercially available CMS solutions have large quantification errors on controlled releases,[15–17] but their detection capabilities show promise, especially for larger emissions.[17] Therefore, while quantification capabilities evolve, CMS can complement snapshot measurements by bounding the duration of detected emissions. The current reporting threshold for large emissions is 100 kg/hr under the proposed EPA rule, but bounding the duration of smaller emissions may become important in the near future, which becomes increasingly challenging for satellites as the size of the relevant emissions decreases.

While it is possible for the proposed duration model to overestimate emission durations, the degree of overestimation would be, in most cases, orders of magnitude smaller than duration estimates from, e.g., quarterly snapshot measurements. Furthermore, the proposed model assumes a single emission source at any given time, which breaks down on larger, more complex sites with consistent background emissions. The ability to localize multi-source emissions will be necessary for accurate duration estimates on these sites, and methods to do so are currently under development.

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Competing Interests

One of the authors (D.M.H.) previously received research funding from a continuous monitoring technology vendor.

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Supporting Information Available

The following files are available free of charge.

- Supporting Information: Contains additional details about the controlled release experiment and the case study.
- Code and data are available at: `https://github.com/wsdaniels/CMS-durations`

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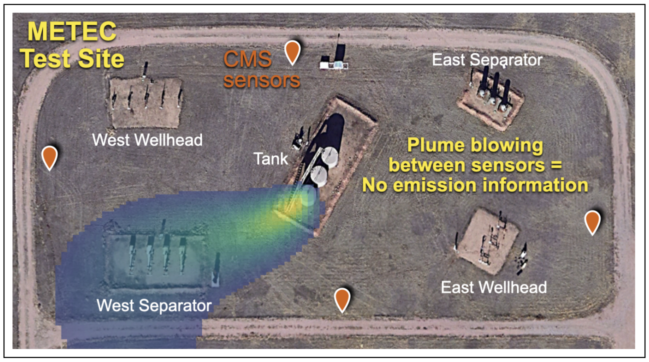
TOC Graphic


METEC
Test Site
CMS
sensors
East Separator
West Wellhead
Tank
Plume blowing
between sensors =
No emission information
East Wellhead
West Separator