Detection, localization, and quantification of single-source methane emissions on oil and gas production sites using point-in-space continuous monitoring systems

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Abstract

We propose a generic, modular framework for emission event detection, localization, and quantification on oil and gas production sites that uses concentration data collected by point-in-space continuous monitoring systems (CMS). The framework uses a gradient-based spike detection algorithm to estimate emission start and end times (event detection) and pattern matches simulated and observed concentrations to estimate emission source location (localization) and rate (quantification). We test the framework on a month of non-blinded, single-source controlled releases ranging from 0.50 to 8.25 hours in duration and 0.18 to 6.39 kg/hr in size. All controlled releases are identified and 82% are localized correctly. 5.5% of predicted events are false positives. For emissions \( \leq 1 \) kg/hr, the framework underestimates by 37.2% on average, with 90% of rate estimates within a factor of [-4.6, 2.8] or a percent difference of [-78.1%, 178.6%] from the true rate. For emissions \( > 1 \) kg/hr, the framework overestimates by...
1.5% on average, with 90% of rate estimates within a factor of [-2.0, 1.8] or a percent difference of [-49.6%, 77.4%]. Potential uses for the proposed framework include near real-time alerting for rapid emissions mitigation and emission quantification for data-driven inventory estimation on production sites.

**Keywords:** methane emissions, oil and gas, continuous monitoring systems, event detection, localization, quantification

**Synopsis:** We create a generic framework that uses methane concentration data from continuous monitors to estimate emission timing, location, and rate.

1 **Introduction**

Reducing methane emissions is a key component of short-term climate action and would greatly increase the feasibility of the 1.5 degree temperature goal from the 2015 Paris Climate Agreement.\(^1,2\) The oil and gas sector accounts for 22% of global anthropogenic methane emissions\(^3,4\) and 32% within the U.S.,\(^5\) and hence it provides a promising avenue for emissions reduction.

Recent attention and advances in measurement technology have revealed a number of important characteristics of methane emissions from the oil and gas sector. First, emissions exhibit high temporal variability, with intermittent events such as liquids unloadings and blowdowns representing a significant portion of total emissions.\(^2,6-9\) Second, emissions can vary by orders of magnitude across basins and sites.\(^10-12\) Third, infrequent super-emitter events can represent a large portion of total emissions, and hence measuring these events is critical for accurate emissions accounting.\(^10,13,14\) Bottom-up inventories have been found to underestimate total emissions and are poorly suited to accommodate these complicated emission characteristics.\(^15-20\) Therefore, direct measurements are needed to better understand and mitigate emissions. In fact, the Inflation Reduction Act will soon require that all reported methane emissions from the United States oil and gas sector are derived from
empirical data rather than conventional bottom-up inventories.²¹

A range of methane measurement technologies exists, including satellites, aircraft, and ground-based continuous monitoring systems (CMS). Satellites with publicly available data have detection thresholds around 1,400 kg/hr in ideal conditions²² and 5,000 kg/hr in more complex conditions,²³ meaning that they can only detect very large emissions. Satellites designed to target specific locations have lower detection thresholds of around 200 kg/hr, but the data is (for the most part) not publicly available.²² Aircraft-based measurement technologies have a much lower detection threshold of around 3 kg/hr and provide mostly unbiased emission rate estimates,²⁴–²⁶ but they occur too infrequently in practice to consistently capture intermittent, short-lived emission events. CMS take measurements in near real-time and have detection thresholds ranging from less than 1 kg/hr (this work) to 3-6 kg/hr,²⁷ making them a promising avenue for measurement-based emissions information in near real-time.

There are three broad classes of CMS: solutions that create actionable information using (1) a sensor network that provides point-in-space concentration observations at fixed time intervals, (2) scanning lasers to measure long, integrated open-path concentrations, and (3) cameras to create 2D images of concentration enhancements.²⁷,²⁸ In this work, we propose a new analytical framework that performs methane emission detection, localization, and quantification using data from the first class of CMS listed above. The framework has two primary use-cases: (1) alerting, in which localization and quantification estimates are provided to the operator in near real-time, and (2) inventory development, in which quantification estimates are used in aggregate to determine cumulative emissions at a given cadence. The proposed framework is best suited for production sites that are around 150m in diameter and contain distinct equipment groups (e.g., wellheads, separators, and tanks).

A number of groups have proposed similar techniques for emission localization and quantification in this setting. Some of these solutions rely on a large sensor network (20 plus), which would be cost prohibitive in practice,²⁹,³⁰ or on long term (multiple hours to days)
aggregates, which would be unable to identify short-lived events, even if they are large.\textsuperscript{31,32} Additionally, many solutions rely on the Gaussian plume atmospheric dispersion model for modeling atmospheric transport.\textsuperscript{30,33} The Gaussian plume model is optimized for far-field applications with distance scales much larger than the typical production site and assumes steady state wind conditions over short (\(~\sim 10\) minute) time intervals, an assumption that breaks down in many practical scenarios where wind conditions are variable. On the other end of the complexity spectrum, some solutions rely on large eddy simulations for modeling atmospheric transport.\textsuperscript{29,34} These simulations are far more accurate than the Gaussian plume model but require special expertise to operate and implement for specific sites, are computationally expensive, and are not generally publicly available. Finally, none of the solutions discussed here attempt to perform emission event detection, and hence they are all tested in rounds with known start and stop times.\textsuperscript{29–34} Note that proprietary solutions are developing rapidly in the private sector, which we are unable to assess.

The event detection, localization, and quantification framework proposed here contributes a number of advancements to this body of literature. First, the framework includes a novel spike detection algorithm that creates a local background estimate for each spike identified in the concentration time series. This algorithm is used in multiple steps of the broader framework. Second, the framework requires no information on emission start or end times to operate. The framework can be run continuously and will only estimate emission location and rate if an emission event is detected (via the spike detection algorithm). Third, the framework uses a Gaussian puff atmospheric transport model that provides a balance between simpler models whose assumptions are rarely met in practice (e.g., the Gaussian plume) and more complex simulations that are computationally expensive and may require customization for different locations. Fourth, with the goal of providing rapid alerts, the framework can provide a location and rate estimate using as little as 15 minutes of data. Finally, the framework does not require an expansive sensor network, but rather can operate using only as many sensors as are required to surround all potential emission sources on the site (approximately
4-8 sensors). Note that the proposed framework can be applied to data from any sensor network that provides point-in-space methane concentration, wind speed, and wind direction measurements.

We test the framework on approximately one month of non-blinded, single-source controlled releases at the Methane Emissions Technology Evaluation Center (METEC) during a range of meteorological conditions. Note that the controlled release data used to evaluate the framework were not blinded, meaning that the controlled release locations and rates were provided to us along with the raw concentration data. Therefore, further blinded testing is needed to more rigorously assess framework performance. That being said, we use the controlled release data solely for framework evaluation in this work. While there are a number of input parameters to the framework, they control site-agnostic settings and were not optimized using the controlled release data. See Section S1 in the supporting information (SI) file for a list and sensitivity study of framework parameters.

2 Methods

Here we describe the two main contributions of this work: (1) a gradient-based spike detection algorithm and (2) a modular framework for methane emission event detection, localization, and quantification.

2.1 Spike detection algorithm

We present an algorithm for flagging sharply elevated values (“spikes”) in a univariate time series, which we assume to be methane concentrations. This algorithm is used in the broader event detection, localization, and quantification framework to estimate background methane concentrations, determine when an emission is occurring, and isolate time steps in which a given sensor is recording a relevant signal.

The algorithm proceeds as follows. Iterate once through the univariate time series. When
an observation is “going up threshold” parts per million (ppm) greater than the previous observation, start a spike. Remain in the spike until the concentration values return to “return threshold” percent of the maximum concentration encountered during the spike. After exiting the spike, average the concentration values immediately preceding and following the spike and use this value as the background estimate for the spike, which imposes no assumptions on the spatial or temporal homogeneity of the methane background. Subtract the background estimate from all observations within the spike, and if the maximum background-corrected concentration in the spike is less than “amplitude threshold” ppm, discard the spike.

This loop results in a mask that records if each entry in the concentration time series is a spike or background. The algorithm relies on three parameters: (1) the going up threshold in ppm, which is used to identify the start of an event, (2) the return threshold as a percent, which is used to identify the end of an event, and (3) the amplitude threshold in ppm, which is used to filter spikes by their background-corrected amplitude. We set these parameters to 0.25 ppm, 5%, and 1 ppm, respectively, after testing the algorithm on months of raw concentration data from multiple production sites. No controlled release data were used to set these default values. The algorithm requires only a single loop through the methane concentration time series, and hence it can be run on historical or real-time data. See Section S3 in the SI file for a detailed description of the spike detection algorithm.

2.2 Event detection, localization, and quantification framework

We now propose a framework for emission detection, localization, and quantification. We design the framework to be highly modular, meaning that it is broken up into distinct steps that can be executed using any number of metrics or methods. Again, the framework is generic and works with any sensor network that provides point-in-space methane concentration, wind speed, and wind direction measurements. Note that the quality of the sensor data (i.e., accuracy and precision) will impact the quality of the framework output, but for
brevity, we do not analyze or discuss this point further in this work.

At a high level, the framework pattern matches methane concentration observations from the CMS to simulation predictions assuming different potential sources. For each identified emission event, the potential source whose simulation most closely matches the CMS observations is taken to be the estimated source for that event. We then estimate emission rate by minimizing error between the simulation predictions from the most likely source and the CMS observations. We only produce a rate estimate when there is reasonably good alignment between the simulation and CMS observations, a measure we have found useful in practice given that the framework relies on an atmospheric transport model that does not directly model turbulence. The framework is broken up into four steps that are described in Sections 2.2.1 through 2.2.4.

Note that while event detection, localization, and quantification can be framed as an inverse problem, we do not perform a full inversion to retrieve source location and emission rate. Instead, we greatly reduce the dimension of the problem by specifying potential emission sources. Doing so is a useful choice in practice on oil and gas production sites, as potential emission sources are often well-known (e.g., tank thief hatches, separators, and wellheads). This procedure would introduce quantification error if emissions originate from a source that is not specified in advance, but it is very often feasible to identify all potential on-site emission sources on the production sites studied in this work.

2.2.1 Remove background and perform event detection

The simulated methane concentrations described in the following section do not include background concentrations that are present in the atmosphere. Therefore, we must first remove background concentrations from the CMS observations before comparing them to simulation predictions. We do so for each sensor separately by using the spike detection algorithm proposed in Section 2.1. Summarizing this procedure at a high level, we group identified spikes that are close together in time, background correct each group using the
concentration observations immediately preceding and following the group, and then set all observations that are not in a group to zero.

Next we define time intervals over which to perform localization and quantification. We do so by taking the minute-by-minute maximum across the background-corrected concentration time series from each sensor, which collapses the signal from each sensor into one time series that captures the concentration spikes across the entire site. If the sensors sufficiently surround the site, then any on-site emission will cause an enhancement in this maximum value time series, regardless of wind direction. Since all non-spike observations have already been set to zero during background removal, we define groups of non-zero values in this maximum value time series as emission events. As a last step, we combine events that are separated by less than 30 minutes, as there are often small gaps between concentration enhancements that do not correspond to gaps in emissions, but rather to periods in which the methane plume is being blown between sensors. We then discard events that are less than 15 minutes long, as these events typically correspond to noise rather than actual emissions. See Section S4 in the SI file for details and an alternative method for defining time intervals that is better suited for more complex sites.

2.2.2 Simulate methane concentrations at sensor locations

We now simulate methane concentrations at each sensor location during the events identified in the previous step. We run a separate simulation for all potential sources on the oil and gas site, which allows us to pick the most likely source for each event in the following step. The framework is not intrinsically tied to any atmospheric transport model, and for this paper we select the Gaussian puff model as a balance between simulation accuracy and computational expense, availability, and ease of use. This model approximates a continuous release of methane from a point source as a sequence of many small “puffs,” each of which is modeled using a three-dimensional Gaussian-like function. This provides a reasonable approximation of atmospheric transport within a short time period after release and over short distances.
barring any major obstructions that would block the transport of methane (e.g., a large building), and hence we think it is suitable for use in our framework when applied to oil and gas production sites.

Predicted concentrations from the Gaussian puff model are a linear function of the selected emission rate, meaning that the pattern of the predictions does not depend on the choice of emission rate. Therefore, we simulate with an arbitrary unitary emission rate (1 g/s), as true emission rates are unknown in practice. With this in mind, we design the pattern matching step described in Section 2.2.3 to be scale-independent by evaluating patterns between observations and predictions rather than overall amplitudes. However, to avoid issues with code-internal quality check thresholds, the simulated concentrations should be on approximately the same order of magnitude as the sensor observations. We have found that simulating with an emission rate of 1 g/s works well on typical production sites, but a larger value may be better if, e.g., the sensors are located extremely close to an extremely large emission source. An error handling check has been built into the code that alerts the user when an adjustment to the simulation scale is recommended.

Section S5 in the SI file and Jia et al.\textsuperscript{35} contain a detailed description of the Gaussian puff atmospheric dispersion model and our implementation for use in the framework proposed here.

### 2.2.3 Source localization

We now estimate the source for each emission event identified in Section 2.2.1. For each event, the potential source whose simulation predictions most closely match the actual CMS observations is taken to be the estimated source. As mentioned in Section 2.2.2, the true emission rate is unknown in practice, and hence we simulate with a unitary emission rate and pattern match using a scale-independent metric.

For each potential source, we compute the correlation coefficient between a stacked vector of simulation predictions at all sensor locations and a stacked vector of the corresponding
background-corrected CMS observations. This results in a correlation value for each potential source for all identified emission events. For each emission event, the source with the highest positive correlation is taken to be the localization estimate for that event. Correlation coefficient is a natural choice for the evaluation metric used in this step, but we also tested a custom metric that rewards spike alignment and penalizes spike misalignment. We discuss these metrics in more detail and present a sensitivity study in Section S2 of the SI file.

2.2.4 Emission rate quantification

We now estimate emission rates by comparing the amplitude of the CMS observations to the amplitude of the simulation predictions, assuming the localization estimate from Section 2.2.3. We only perform this comparison using time steps in which both the observations and predictions are in a spike, which we identify using the spike detection algorithm described in Section 2.1. This drastically reduces the impact of transport model inadequacies on the emission rate estimate and in part justifies the use of a relatively simple model. If there are at least four time steps during which both the observations and predictions are in a spike, then a rate estimate is computed for that emission event. Otherwise, we deem the event unsuitable for quantification. We require at least four instances of spike alignment because it helps prevent single instances of notable model error from dominating a given emission rate estimate. Note that the framework is not highly sensitive to this threshold, meaning that slightly different values do not result in drastically different rate estimates. See Section S1 in the SI file for more details and the full sensitivity study.

For each identified emission event, we sample with replacement 1000 times from the time steps in which both predictions and observations are in a spike. For each sample, we minimize a loss function over a range of emission rates between a stacked vector of simulation predictions at all sensor locations and a stacked vector of the corresponding background-corrected CMS observations. This optimization can be done using the simulation output from Section 2.2.2, as the Gaussian puff dispersion model is a linear function of emission
rate. Hence, to compute simulation predictions at an arbitrary emission rate, $q$, we simply need to multiply the predictions simulated with a unitary rate by $q$. Four different loss functions were tested, with root-mean-square error (RMSE) having the best performance. See Section S2 in the SI file for a discussion and sensitivity study of the four loss functions we considered. The overall rate estimate for the event is then taken to be the mean of the sample-specific rate estimates.

There are two reasons why we perform this sampling procedure rather than simply minimizing RMSE between predictions and observations. First, it reduces the impact of time steps in which there is notable model error on the resulting rate estimate, as many samples will not include this time step. Second, the spread of the sample-specific rate estimates provides uncertainty quantification on the overall rate estimate. Specifically, we set the error bound on the overall rate estimate as the 5th and 95th percentiles of the sample-specific rate estimates. This approach does not impose any assumptions on the symmetry of the error bound.

3 Results

We evaluate the framework proposed in Section 2 using data collected by Project Canary\textsuperscript{36} CMS sensors at the Methane Emissions Technology Evaluation Center (METEC) in Fort Collins, Colorado during the Advancing Development of Emissions Detection (ADED) research program.\textsuperscript{37} Note that the controlled release data used in this paper are not blinded, which is a deviation from the ADED protocol. METEC is a testing center that resembles an oil and gas production site and performs controlled methane releases from multiple pieces of equipment.

We focus on roughly one month of controlled releases during which there are primarily single-source emissions (April 17 to May 16, 2022). This study period contains 85 single-source controlled releases ranging from 0.50 to 8.25 hours in duration and 0.18 to 6.39 kg/hr
in size. Emission rates are constant during each release. Releases have variable start and end times and are separated by periods of no emissions with different durations. Emissions can come from one of five potential emission sources, indicated with colored boxes in Figure 1. We assume that the release point for the tanks is at a height of 4.5 m and the release point for all other sources is at a height of 2 m. Note that there are seven multi-source emission events during this study period, which we exclude from all further analysis. Future work will introduce methods for quantifying multi-source emissions.
Figure 2: Detection, localization, and quantification results over the one month study period from April 17 to May 16, 2022. Controlled release events are indicated with solid rectangles, with the height of the rectangle corresponding to the true emission rate and the color corresponding to the true source. Timing and location of estimated events are indicated with transparent rectangles, with color corresponding to the estimated source. The heights of the transparent rectangles are fixed at an arbitrary value for visual clarity. Estimated emission rates and error bounds are indicated with black circles and lines, respectively.
Methane concentrations are measured by eight CMS sensors placed around the perimeter of the METEC site at a height of 2.4 m, three of which also measure wind speed and direction. Note that additional higher sensors would be needed if very tall emission sources were present (e.g., flare stacks). Sensor locations are marked with pins in Figure 1. Project Canary used a Near-IR Tunable Diode Laser Absorption Spectroscopy (TDLAS) methane sensor and an R.M. Young 2D ultrasonic anemometer during the ADED controlled releases. The methane sensor has a stated accuracy of $\pm 2\%$ and precision of $\leq 0.125$ ppm. The anemometer has a stated accuracy of $\pm 2\% \pm 0.1$ m/s for wind speed and $\pm 2$ degrees for wind direction and a stated precision of 0.01 m/s for wind speed and 0.1 degrees for wind direction. Methane concentration, wind speed, and wind direction are measured every second and are averaged every minute by Project Canary, resulting in one data point per minute.

We assume a homogeneous wind field across the site, and hence we take the minute-by-minute median of the wind speed and direction data across the three sensors that measure these variables (taking into account the fact that wind direction is a circular variable). We found that using the median reduces the impact of sensor noise compared to the mean. See Section S6 in the SI file for details on our wind data processing scheme.

Figure 2 provides an overview of the timing, source, and emission rate for each of the 85 single-source emission events along with the event detection, localization, and quantification results from the proposed framework. The remainder of this section will discuss specific aspects of the framework’s performance.

We first consider timing and minute-by-minute event detection performance. Most emission start times are predicted accurately, with a median start time error of 4 minutes (meaning the predicted start time came 4 minutes late) and a distribution tightly centered around the median ($25^{\text{th}}$ percentile = 1 minute and $75^{\text{th}}$ percentile = 11 minutes). Similarly, most end times are predicted accurately, with a median end time error of zero minutes and a distribution tightly centered around the median ($25^{\text{th}}$ percentile = -1 minute and $75^{\text{th}}$ percentile = 2 minutes). Overall, the framework correctly predicts the presence or absence of
We now consider a number of event-level performance metrics, which are summarized in Figure 3. The framework correctly identifies 100% of emission events, with 93% deemed suitable for quantification. Furthermore, 89% of emission events overlap with at least one predicted emission event that was correctly localized and 82% have a completely correct localization estimate. The performance in all four categories is largely consistent across the source locations. This level of event detection and localization performance suggests that the framework could be used to provide informative alerts to operators when emissions are occurring on production sites similar in complexity to METEC.

We now consider quantification performance. Figure 4 shows a parity plot of the true
Figure 4: Parity plot of true (horizontal axis) and estimated (vertical axis) emission rates. Point color and symbol correspond to the true emission source. Points falling on the 1:1 line are perfect estimates. Points between the black dashed lines are within a factor of two of the true rate. Points between the black dotted lines are within a factor of three of the true rate. Points along the vertical solid gray line are false positives, and points along the horizontal solid gray line are false negatives. Points along the horizontal dot-dashed gray line are emission events that were identified but were not deemed suitable for quantification. The magenta line shows the linear model fit to all correctly identified events (i.e., true positives only) using ordinary least squares. One estimate of 14.4 kg/hr corresponding to a METEC emission of 4.9 kg/hr is excluded for visual clarity. Uncertainty in the METEC emission rates is a 95% confidence interval provided by METEC. The right panel zooms in on data shown in the left panel.

and estimated emission rates, with the true rate plotted on the horizontal axis and the corresponding estimate on the vertical axis. Ordinary least squares is used to fit a line to all of the correctly identified events (i.e., true positives only), which can be used as one measure of overall bias in the estimates. Estimates for the larger emissions (> 1 kg/hr) appear much less biased than estimates for the smaller emissions (≤ 1 kg/hr), where we see systematic underestimation. This suggests that the framework is better able to quantify larger emissions, which is expected as these emissions have a stronger signal (more separation
Figure 5: Relative error between estimated and true emission rate, separated by small (≤ 1 kg/hr) and large (> 1 kg/hr) true emission rates. Factor difference is shown on the bottom axis, with negative values corresponding to underestimation, and percent difference is shown on the top axis. Note the different scales between the two subfigures. Vertical gray lines show the error bounds of the middle 50, 75, and 90% of all individual estimates, and vertical red line shows the median error. Darker shading indicates underestimation and lighter shading indicates overestimation.

From baseline and noise) and hence should be easier to quantify. Note that true emission rate is the primary driver of quantification accuracy. There is very little relationship between quantification error and emission duration, wind speed, or wind direction variability. See Section S9 in the SI file for details.

Figure 5 further explores the difference in quantification accuracy between small (≤ 1 kg/hr) and large (> 1 kg/hr) emissions. Subfigures (a) and (b) show histograms of the relative error between estimated and true rates for small and large emissions, respectively. The factor difference is shown along the bottom axis, with negative values meaning underestimation, and percent difference is shown along the top axis. Both factor and percent difference are measures of relative error, but unlike percent difference, factor difference is not bounded by -100% and hence we think better captures underestimation error. Note that a factor difference of 1 indicates perfect alignment, while a percent difference of 0% indicates perfect alignment.
Estimates for small emissions tend to underestimate, with a median factor difference of -1.59 (-37.2%). Estimates for large emissions are nearly unbiased with a very slight tendency to overestimate, having a median factor difference of only 1.01 (1.5%). For small emissions (\(\leq 1 \text{ kg/hr}\)), 90% of the estimates have error within a factor difference of [-4.6, 2.8] or a percent difference of [-78.1%, 178.6%] from the true rate. The performance is markedly better for the large emissions (\(> 1 \text{ kg/hr}\)), where 90% of the estimates have error within a factor difference of [-2.0, 1.8] or a percent difference of [-49.6%, 77.4%] from the true rate.

Finally, we consider cumulative quantification error over the one-month study period. When considering only small emissions (\(\leq 1 \text{ kg/hr}\)), the framework underestimates cumulative emissions by 41.9%. When considering only large emissions (\(> 1 \text{ kg/hr}\)), the framework overestimates cumulative emissions by 0.8%. These percent differences are close to the median bias values discussed earlier (-37.2% for small emissions and 1.5% for large emissions), which is expected, as there were no event-level false negatives during the one-month study period. The presence of false negatives would cause the gap between estimated and true cumulative emissions to be larger than the median bias values, as the bias values are based on correctly identified events only. Overall, when including both false positives and false negatives and both small and large emissions, the framework underestimates cumulative emissions by 6.7%. See Section S10 in the SI file for details.

4 Discussion

We propose an analytical framework for the detection, localization, and quantification of single-source methane emissions on relatively simple oil and gas production sites. When tested on single-source, non-blinded controlled release data, all releases are detected and 82% are localized correctly. For emissions \(> 1 \text{ kg/hr}\), quantification from the framework is unbiased and 90% of estimates are within a factor of [-2.0, 1.8] or a percent difference of [-49.6%, 77.4%] from the true rate. Note that further blinded testing is needed to more
rigorously assess framework performance.

Applying this framework to larger, more complex sites (e.g., midstream compressor stations) will likely require a more nuanced monitoring and modeling approach. Large buildings and equipment groups block the transport of methane and introduce downwash effects, both of which are not captured by the Gaussian puff model, and hence a more sophisticated atmospheric transport model may be necessary for these sites. Furthermore, a single ring of sensors around the perimeter of larger sites will likely provide insufficient signal separation, as it becomes harder to distinguish between two nearby sources the further away the sensors are placed. Hence, for monitoring purposes, such sites may need to be divided into smaller sectors that are each surrounded by sensors.

Additionally, multi-source and off-site emissions pose important challenges that are outside the scope of this paper. Addressing these more complex emission scenarios is left to future work, but we briefly discuss some high-level thoughts here. Multi-source emissions could be modeled as the sum of two or more single-source emissions (as predicted concentrations from the Gaussian puff model are linearly additive), and hence would require no additional simulations to accommodate. However, this will notably increase the search space during localization and quantification and requires further study to assess practical feasibility. Off-site emissions are an important consideration for dense production settings (e.g., the Permian basin) and could be identified by incorporating potential off-site sources during the simulation step. The fidelity of this strategy would need to be balanced against the extra computational cost of simulating from many additional sources.

Despite these limitations, the proposed framework in its current form has two clear use-cases on relatively simple oil and gas production sites: (1) alerting, where localization and quantification estimates are provided to the operator in near real-time, and (2) inventory development, where quantification estimates are used in aggregate to determine cumulative emissions at a given cadence. The variability of individual rate estimates does not detract from the applicability of the framework in these use-cases. For alerting, the ability to generate
continuous emission estimates with localization in near real-time is more pertinent than the exact rate estimate, as the main purpose of alerts is to give the operator enough information to decide if further investigation is necessary. If a large rate estimate is consistently localized to a given equipment group every, e.g., 15 minutes, then the operator can be fairly confident that an emission is indeed occurring, regardless of the exact rate estimates that are being generated. For inventory development, the average of many individual rate estimates will be used to produce an overall estimate for the site at a, e.g., monthly or yearly cadence. This means that variability in the individual estimates will be averaged out and the overall bias in the estimates will drive the accuracy of the inventory. Large emissions make up a large portion of total emitted volume, and hence the proposed framework’s negative bias for small emissions $< 1$ kg/hr would, in most situations, be outweighed by its unbiased nature for larger emissions if used for inventory development.

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Supporting Information Available

The following files are available free of charge.

- Supporting information: additional details on framework operation and performance.

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TOC Graphic