Drive-Around Surveys for Detection and Quantification of Methane Leaks

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Methane Leak Detection

Motivated in part by the anticipation of tightening regulations globally, research and development in methane measurement, reporting, and validation (MMRV) technology has steadily grown in recent years with platforms ranging from ground-based continuous monitoring sensors to satellite-based leak detection solutions. Current MMRV solutions have the potential to quickly survey entire oilfields or detect methane leaks down to the component level, but also carry high price tags or, indirectly, high implementation costs. Fortunately, public incentives through the Infrastructure Investment and Jobs Act and Inflation Reduction Act are working to ameliorate this issue. For example, the U.S. Department of Energy announced in mid-2022 $32 million in funding towards MMRV research with one of its main goals to develop "low-cost, implementable" monitoring solutions.

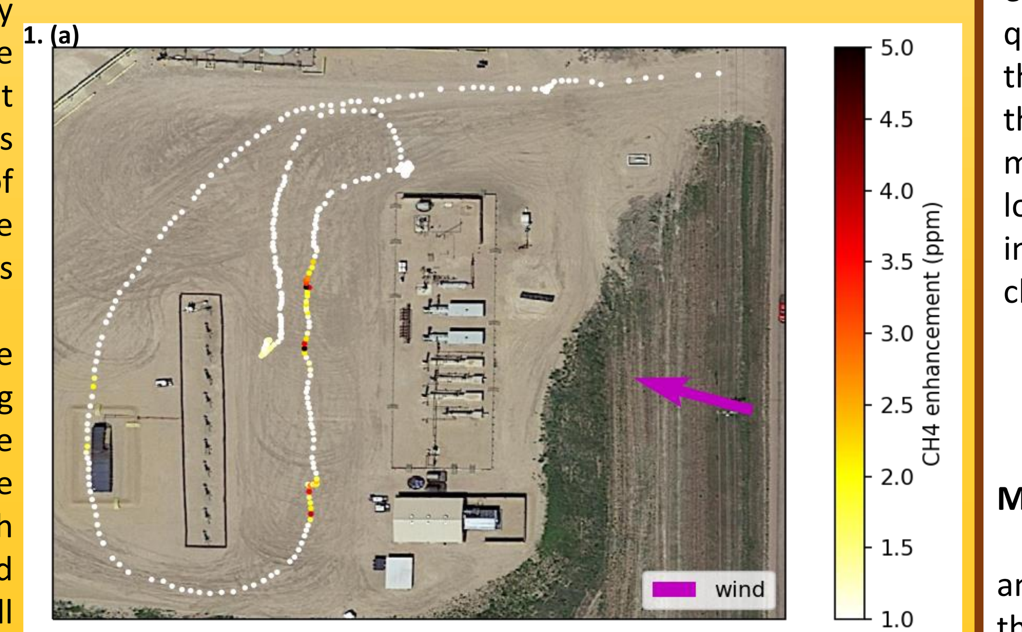
The Stanford/EDF Mobile Monitoring Challenge (MMC) conducted in 2018 was the first study to systematically evaluate methane mitigation technologies for incorporation into LDAR programs at the operator level. Three vehicle-based solutions tested in the MMC utilized a fence-line screening pattern that encompassed a production site and equipment, which we refer to as a "drive-around survey," and showed promising results of greater than or equal to 88% true positive source identification rates for controlled releases in the 0-26 kg CH_4/hr range. In this work, we evaluate a similar on-site drive-around survey as an alternative methane leak detection method under the EPA's recent update to the Standards of Performance for New, Reconstructed, and Modified Sources and Emissions: Oil and Natural Gas Sector (NSPS).

Drive-Around Survey Method

The University of Wyoming mobile laboratory employed in this study is equipped with Aerodyne and Picarro methane analyzers sampling at 1Hz that are sensitive to changes of 1 ppb CH_4. Ambient air is sampled from the instrument mast at a height of 12.5 ft. The instrument mast also holds two mobile weather stations recording meteorological variables such as pressure, temperature, and wind speed.

Upon entering a production site, methane concentrations were sampled in a closed loop along the perimeter of the site. Service and maintenance roads were utilized as best as possible to sample methane concentrations along a closed path around the production equipment and associated wells. Some roads did not allow for full encapsulation of the equipment. Therefore, the survey team ensured that methane concentrations were sampled upwind of the equipment during the screening survey. The typical background noise for CH_4 concentrations in the Denver-Julesburg Basin was observed to be 50 ppb. Therefore, measurable enhancements were defined as methane concentrations greater than 100 ppb above background concentration.

1. (a)



(b)

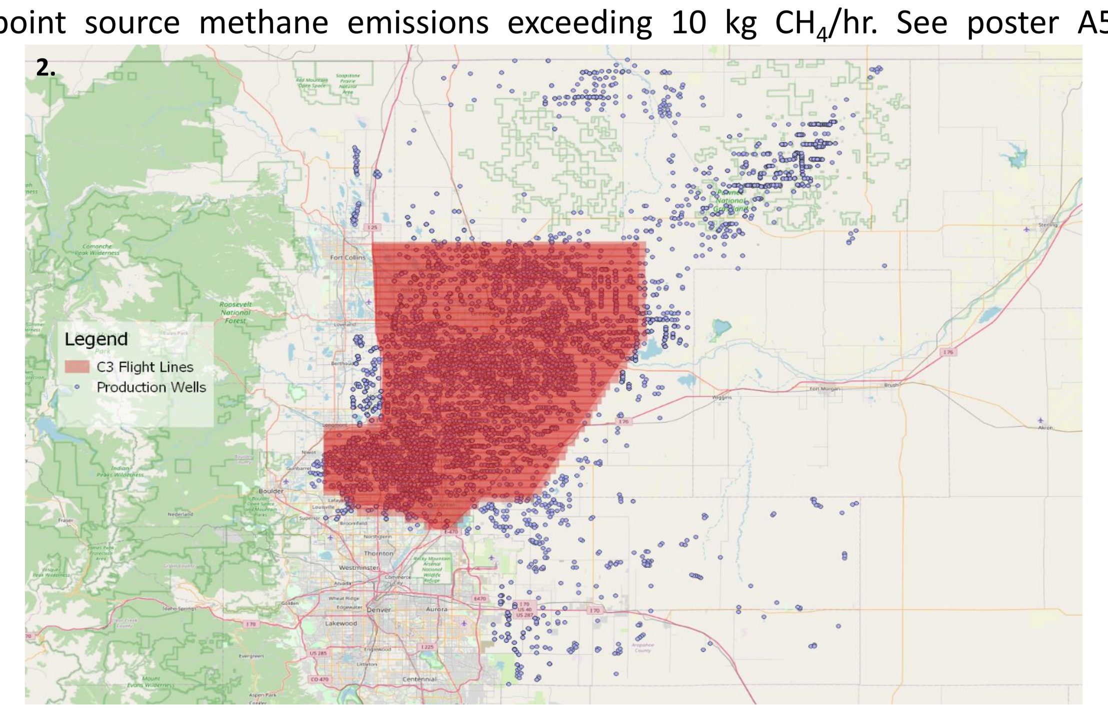
Figure 1: (a) An example of a typical site survey driving pattern on a production well pad. (b) The University of Wyoming mobile laboratory is shown. The vehicle is equipped with a suite of gas analyzers and meteorological instruments.

Colorado Coordinated Campaign (C3)

In the Summer and Fall of 2021, the Colorado Coordinated Campaign (C3) was conducted in the Colorado portion of the Denver-Julesburg (DJ) Basin. The primary objective was to compare modeled emissions from Oil and Gas (O&G) operations to ground-based and aircraft-based emissions measurements. For this campaign, the Mechanistic Air Emissions Simulator (MAES) model, developed by Colorado State University and the University of Texas at Austin, will be utilized to simulate emission events from the O&G upstream and midstream sectors. MAES was developed to narrow the persistent top-down/bottom-up inventory gap by providing insights into the frequency and persistence of large emissions, while offering bottom-up estimates of methane emissions. The study boundary for C3, depicted in Figure 2 below, encompassed assets contributing to approximately 97% of natural gas production in the DJ Basin.

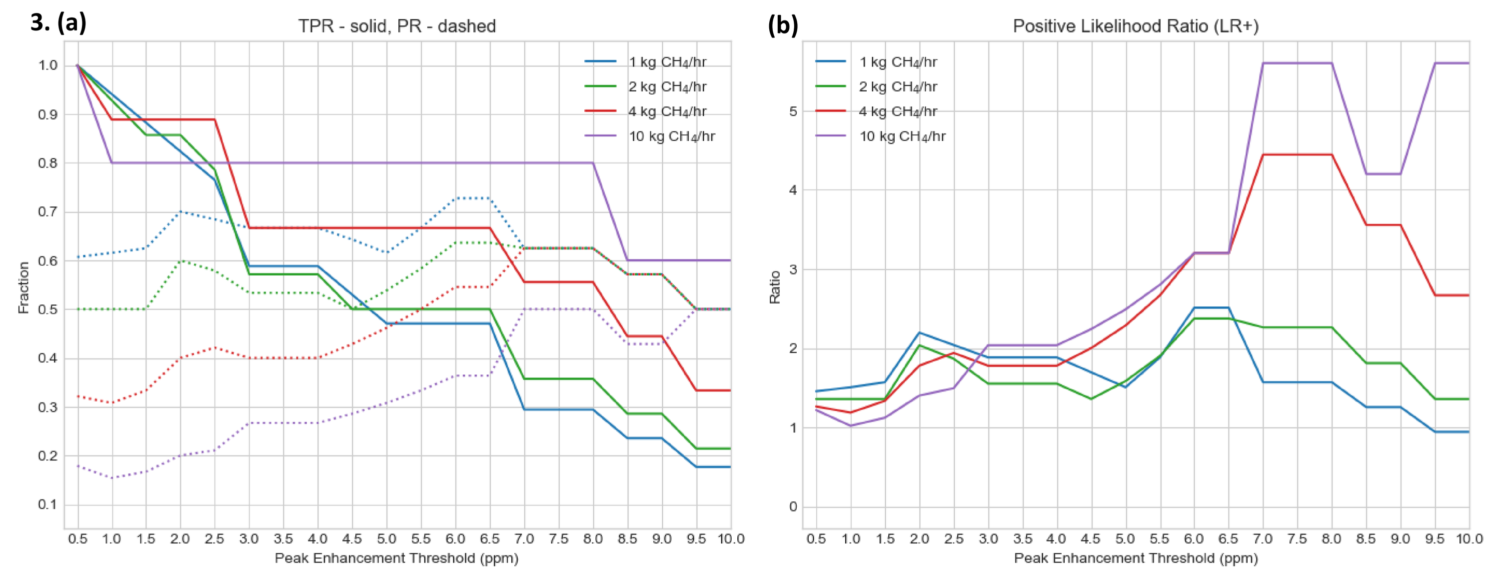
The C3 ground measurement campaign consisted of downwind measurements of facility-level methane emission rates and air canister sampling of production sites for laboratory analysis of CH_4:VOC ratios. The University of Wyoming and Colorado State University mobile laboratory teams surveyed a total of 349 production sites, quantified 44 sites using Tracer Flux and Other Test Method 33a, and collected 98 VOC canister samples. Asynchronously, the CarbonMapper Global Airborne Observatory (GAO) spectrometer repeatedly surveyed the basin to detect point source methane emissions exceeding 10 kg CH_4/hr. See poster A51L-2114 for further information.

2.



Classifying Emission Rates from Drive-Around Surveys

3. (a) (b)



Methane Enhancement Thresholding

Classification performance was evaluated for a naïve detection model based on surveyed methane enhancement, similar to EPA method 21, but in the sensitivity range of today's low-cost sensors. Standard binary classification metrics derived from true/false positives and true/false negatives were used in the evaluation. Figure 3(a) shows this method performs relatively well with true positive rates (TPR) around 80% of quantified emissions in the 1, 2, 4, 10 kg CH_4/hr classes proposed by the EPA. However, the same graph shows the detection precision (PR) is inversely related to the size of leak classes. The positive likelihood ratio (LR+) is the ratio of true positive rate to false positive rate and is used as a pre-test odds multiplier in evaluating medical tests. Figure 3(b) shows the LR+ peaking at 2.5 around the 6 ppm enhancement threshold for the lower emission rates, and LR+ above 4 around 8 ppm for the higher emission rates. This translates to a 4-fold increase in the odds of the emission rate exceeding those emission thresholds when identified by the naïve classifier model.

$$TPR = \frac{TP}{TP + FN}, \quad PR = \frac{TP}{TP + FP}, \quad FPR = \frac{FP}{TN + FP}, \quad LR+ = \frac{TPR}{FPR}$$

Machine Learned Classification

A voting classifier composed of AdaBoosted random forest classifiers was trained on surveyed wind speeds and methane enhancements for the 1 kg CH_4/hr case, as this class had the largest "positive" sample. We found that the true positive rates remained near 80% but saw the precision improving to 80%, suggesting that the incorporation of wind data can boost performance when employed non-linearly.

4.(a) (b)

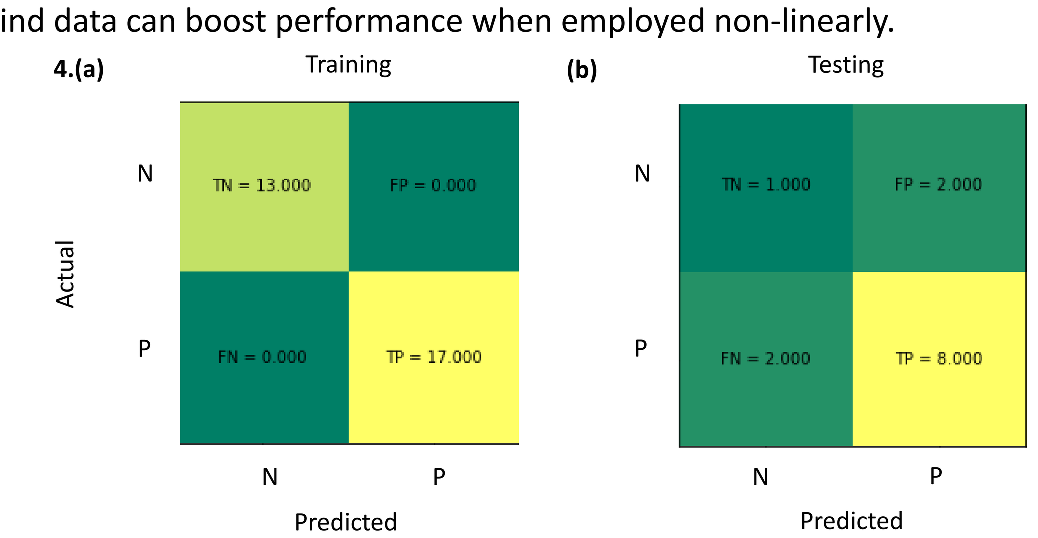
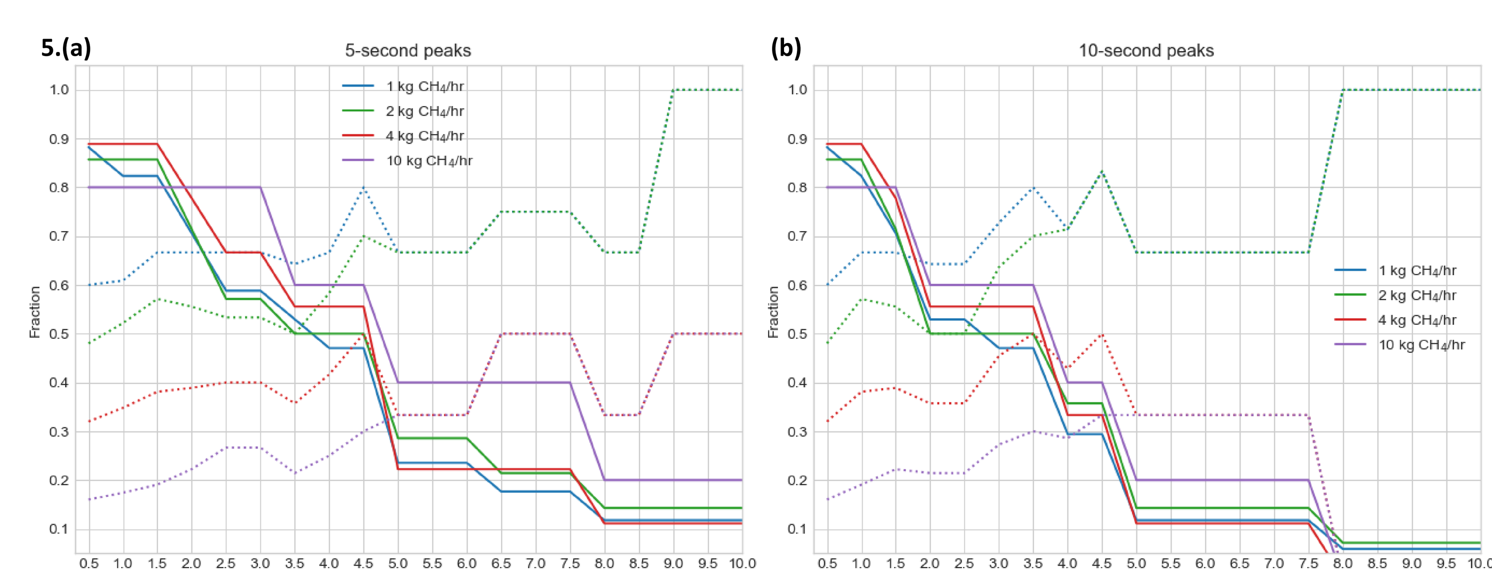


Figure 4: (a) The "confusion" matrix is shown for the training performance of the random forest classifier. (b) The out-of-sample testing performance is shown for the trained random forest classifier. The standard 70/30 train/test split was utilized for this evaluation process.

Instrument Response Time Dependency

Rolling 3, 5, 10, 30 second averages were calculated from the original 1Hz data to simulate slower instrument response times. The TPR and PR evaluation was repeated with the simulated data and shows that the naïve detection model degrades with temporal resolution. Evaluation on 5-second peak enhancements (Figure 5(a)) and 10-second peak enhancements (Figure 5(b)) are shown below. 10 and 30 second averaged data showed the worst performance with virtually no separation of performance metrics at the tested emissions thresholds. These time resolutions are especially pertinent for ultra low-cost metal oxide sensors.

5.(a) (b)



Please scan the QR code to see a list of references.

Estimating Emission Rates from Drive-Around Surveys

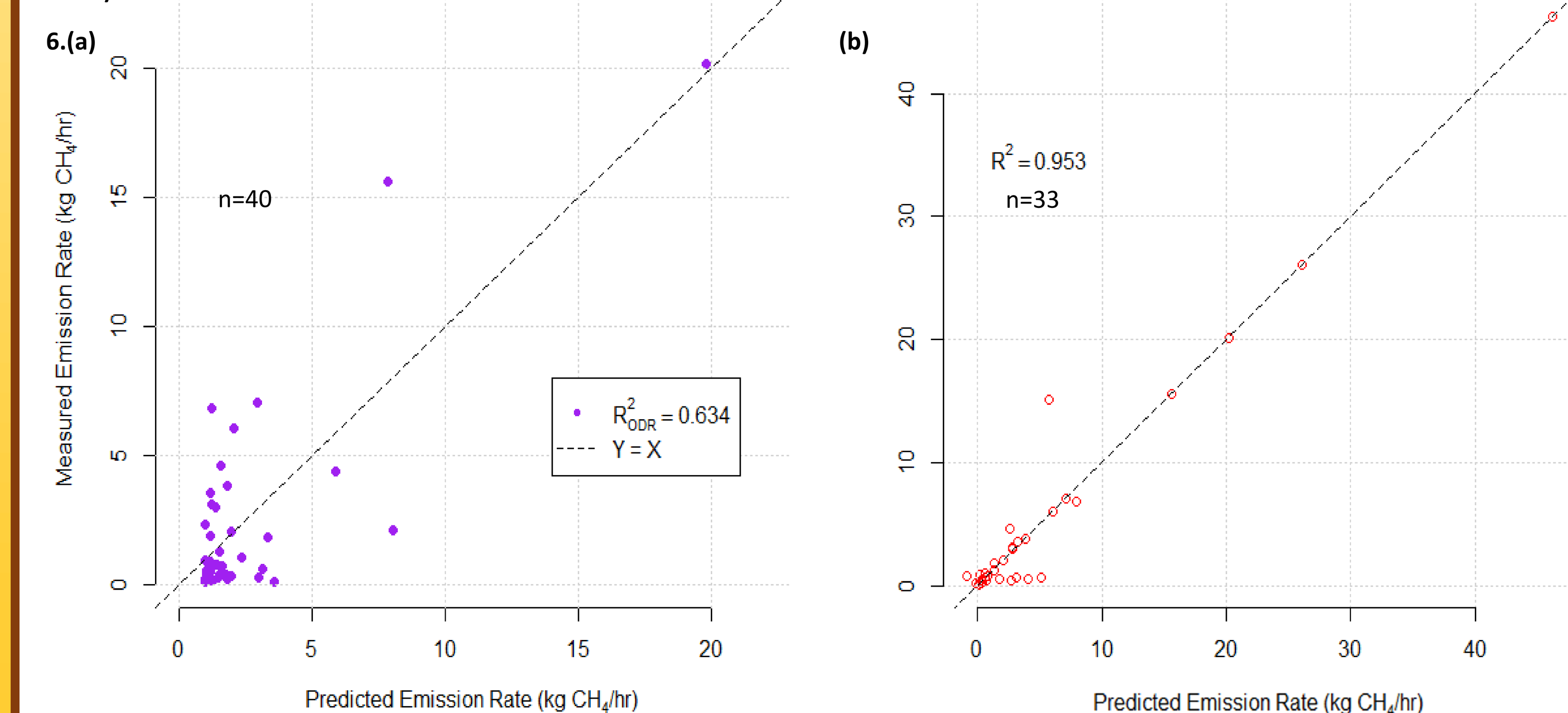
Empirical Inverse Flux Estimation

Based on the Gaussian plume model, a linear model of emission rate (F_x) regressed on the surveyed average wind speed ($\bar{u}$) and peak methane enhancement (C_x) was fitted using 44 surveyed and quantified production sites.

$$F_x = 2\pi\sigma_y\sigma_z\bar{u}C_x \rightarrow F_x = \beta_o + \beta_1(\bar{u}C_x) + \varepsilon$$

Considering that meteorological, gas concentration, tracer flux and OTM33a measurements carry uncertainty, orthogonal distance regression (ODR) was utilized to minimize total distance between data points and the linear model. Seen in Figure 6(a) below, the resulting model explained a considerable portion of the variance ($R^2_{ODR} = 0.634$). This model was applied to each surveyed site and used for the extrapolation of the DJ basin methane flux from O&G production which agreed with 2021 GHGRP estimates. This suggests that drive-around surveys can be utilized to effectively constrain basin-level O&G emissions. See poster A51L-2114 for the in-depth analysis on DJ basin methane flux.

6.(a) (b)



A Heuristic Approach to Dispersion

Standard inverse Gaussian approaches, such as OTM33a, rely on measurement distance from the source and a measure of atmospheric stability to calculate horizontal (σ_y) and vertical (σ_z) dispersion. Anticipating that the drive-around approach will be employed without a range finding instrument, different approaches for estimating dispersion from the 1Hz methane concentration data were investigated. As the difference between the 1, 3, 5, 10, 30 second averaged peaks are related to the width of an individual plume, we the found covariances of these peaks as an efficient proxy for dispersion. Figure 6(b) shows a linear interaction model, which includes the covariances of these peaks, explaining a significantly higher proportion of variance ($R^2 > 0.9$) suggesting that distance information is not required to accurately estimate emission rates.

7.(a) (b)

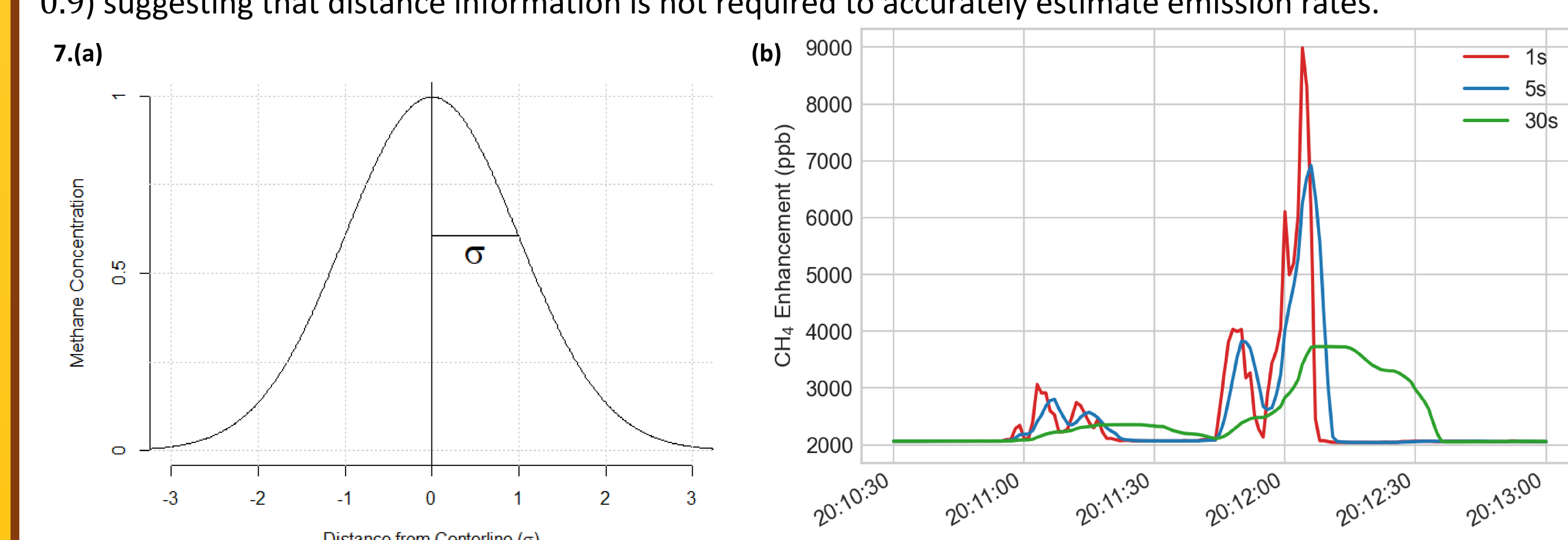


Figure 7: (a) The typical Gaussian curve that is expected when transecting a methane plume is shown. (b) A surveyed plume transect is shown with its upscaled 5 and 30 second averaged data. The covariance of the peaks of these curves can be utilized as a proxy for dispersion (σ).

Alternative Methane Detection Technology

As a standalone technique, our work so far does not show the drive-around survey as meeting the requirements under the new NSPS. Specifically, the NSPS alternative methane detection technology schedule assumes a probability of detection of 90% for prospective leak detection solutions. As most O&G producers already require their employees to perform an Audio, Visual, and Olfactory (AVO) inspection during every site visit, this proposed survey method shows promise as a supplement to AVO inspections for identifying malfunctioning equipment and can serve as a preliminary survey prior to optical gas imaging (OGI) surveys to constrain the physical location of fugitive emissions.

Cost-Effective

This method is competitive with readily available solutions because of its simplicity in methodology and required equipment, which makes it easily integrated into in-house LDAR programs with minimal on-board training. For leaks exceeding 4 kg CH_4/hr, a sensor that is sensitive to within 8 ppm could enable a 4-fold increase in the odds of detection. Many low-cost analyzers on the market are already within this sensitivity.

Future Work

The heuristic approach to dispersion described in this work is a very recent development. As it stands, the linear interaction model shows near perfect skill for estimating emission rates above 5 kg CH_4/hr. The covariances between the 1, 3, 5, 10, 30 second averaged peaks will be incorporated as additional parameters in future training of our ML-based classifiers. Finally, drive-around surveys will be performed in conjunction with O&G facility quantification in the upcoming SABER campaign, resembling a larger scale C3, thereby increasing the sample size on which to validate this method for emission rate detection and quantification.