How to estimate O&G well leak rates from near field concentration and wind observations?

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About 2.3 million orphan oil and gas (O&G) wells exist and are estimated to emit 200G g CH_4 y^{-1} by EPA/Enverus[1] that implies an average CH_4 leak rate of 10 g CH_4 hr^{-1} per well.[1] US government has an aggressive plan to plug orphan wells at costs of around $100K/well. In order to manage the costs of plugging millions of wells, quantifying leaks from individual wells is essential for prioritization. Current methods to quantify leaks require costly hardware, labor-intensive protocols and expensive analysis (Appendix 1 – Table A1).

In order to reduce costs and ease operations we explore the use of direct CH_4 concentration measurements (at sub parts per million, sub-ppm, that is achieved by current solid state and optical sensors as noted in the Figure below) along and across the wind direction close to a point source (i.e. an orphaned well) to infer mass flow rate of methane. The observed CH_4 concentration fields downwind of a point source (i.e. an orphan well), collected under stable wind conditions, together with wind speed measurements could be used to infer its leak rate. This flux inversion can be run using semi-empirical and parameterized Gaussian plume dispersion models (GPDMs) that have been extensively tested and approved by EPA for air pollution and hazard exposure assessments. The parameter tuning of GPDMs has been done at large scales (0.1 to 10s km) for various atmospheric stability classes, surface roughness and plume types. However, the use of GPDMs at small scales (0-10 m) necessary to infer emissions from orphaned wells is a new regime that has not been explored systematically.

In this white paper, we propose a path forward to develop, evaluate and implement this near source GPDM as it can enable cost effective leak rate estimates by harnessing CH_4 and wind measurements with sufficient accuracy to prioritize orphaned wells for plugging.

In order to explore our strategy, a GPDM model developed to simulate a large coal mine vent shaft plume dispersion over a range of 100s meter was used. [2] We believe the GPDM model is most suited for the point source, orphan well leakage scenario.

First, we ran the GPDM model in forward mode to determine concentration as a function of distance from the point source plume (Figure 1). We ran our model for typical stable atmospheric conditions anticipated at an Orphaned well (i.e. steady winds of 3 m/s) for three different source strengths: (1 g/hr; 17 g/hr; 40 g/hr). We assumed a stable boundary layer (Class "F", as the scales are small), and ignored parameters such as surface roughness and buoyancy to simplify the problem. Figure 1 shows the CH_4 concentration as a function of distance for a measurement point directly in the plume centerline, at the same level as the source (z=H=1m).

Our simulations (Figure 1) show that the CH_4 signal near the source is significant but drops exponentially – 100 ppm at source, 20 ppm at 2m and <1 ppm at 10m for the smallest 1 g/hr leak. This spatial feature can be easily measured with current sensors (sub ppm levels as shown in Figure) and the peak CH_4 values scale at the source with its strength and the falloff with distance is steeper for larger leaks.

However, there is also a large sensitivity of our results to the atmospheric stability class that is used to parameterize the plume dispersion coefficients (σ_y and σ_z) at larger scales. Changing stability classes causes large changes in our results. For example, with equal parameters [x=10 m, Q=1 g/hr, and u=3 m/s] an "A" stability class (very unstable atmospheric conditions) yields to 0.9 ppb, and an "F" stability class (very stable atmospheric conditions) gives 0.5 ppm, a 3 order of magnitude difference. The differences can be smaller near the source (0-3 m) and may be better suited to assess empirically point-source strength. Using GPFMs represent a significant source of uncertainty in our current ability to infer emission rates from concentration measurements, even as concentrations are detectable and the fall-off quantifiable.

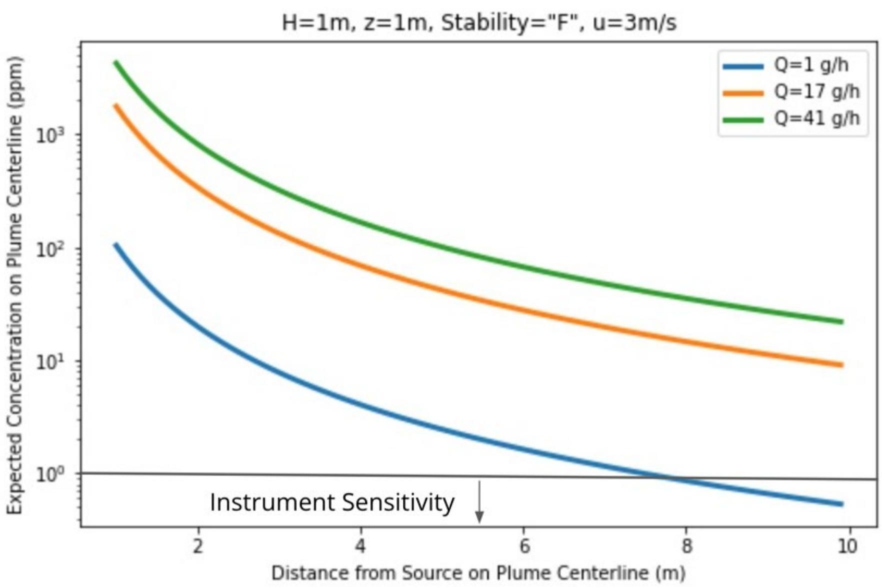

Figure 1: Concentration as a function of distance from the plume centerline.

A simple approach to this challenge could be to measure methane concentrations at a given distance from the known point source under stable atmospheric conditions ("F" stability class), and at a similar height as the height of the point sources for about 5 minutes in order to capture some aspect of the plume structure. The maximum concentrations measured can be used to assess the point source strength based on Table 1 (as an example).

Table 1: Expected methane concentration as a function of wind speed and distance from a 1g/hr point source and stable atmospheric conditions (Class "F").

Wind velocity \ distance	2m	3m	6m	10m
1 m/s	67.2 ppm	25.2 ppm	5.1 ppm	1.6 ppm
3 m/s	22.4 ppm	8.4 ppm	1.7 ppm	0.5 ppm
5 m/s	13.4 ppm	5.0 ppm	1.0 ppm	0.3 ppm

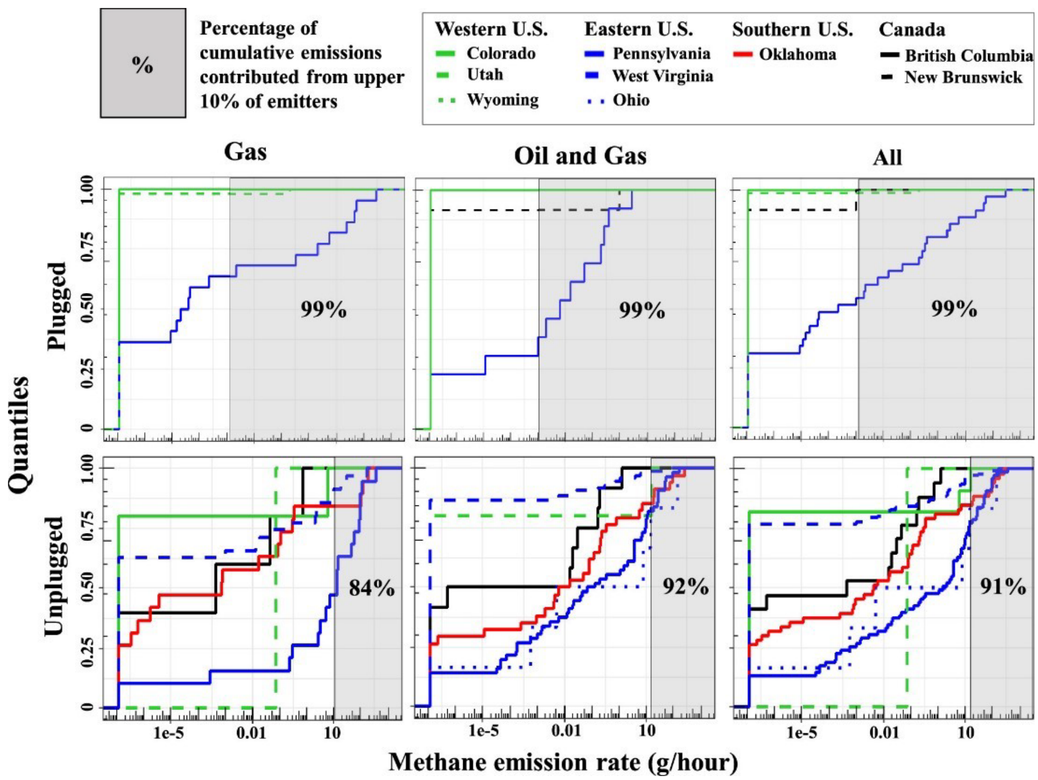

Figure 2: empirical cumulative distributions of measured methane flow rate from plugged (top), unplugged (bottom) abandoned oil, and gas wells in the US and Canada. Each curve represents a state/province. Blue and green curves represent eastern and western states in the US. red curves represent Oklahoma. Black curves represent Canadian provinces. Shaded regions in each plot represent the 90-100th percentile of methane emissions rates for that group, with the annotation showing the percentage of cumulative emissions, the top 10% of abandoned oil and gas wells. (Reprinted with permission from Williams et al. 2021, env.sci.tech. 55(1) 563-570. Copyright American chemical society.

Figure 2 shows the percentage of cumulative emissions for the upper 10% of methane emitters for wells across the United States. The technique we are proposing in this white paper is to address the long, low-emissions tail of the skewed well distribution shown in the figure. The key point is that 90% of the emissions are expected to be from a few wells that emit above 10 g/hr. Wells above this threshold are significant contributors to methane emissions and thus likely merit better, more costly assessments. However, the large number of wells below this threshold but above 1 g/hr are the wells we expect this method to be most impactful. With the reason being that, the measurement cost-benefit for low flow rates relative to the value of that information is simply too high.

Next, we use the GPDM model to develop a relationship between concentrations and flow rates for different wind speeds.

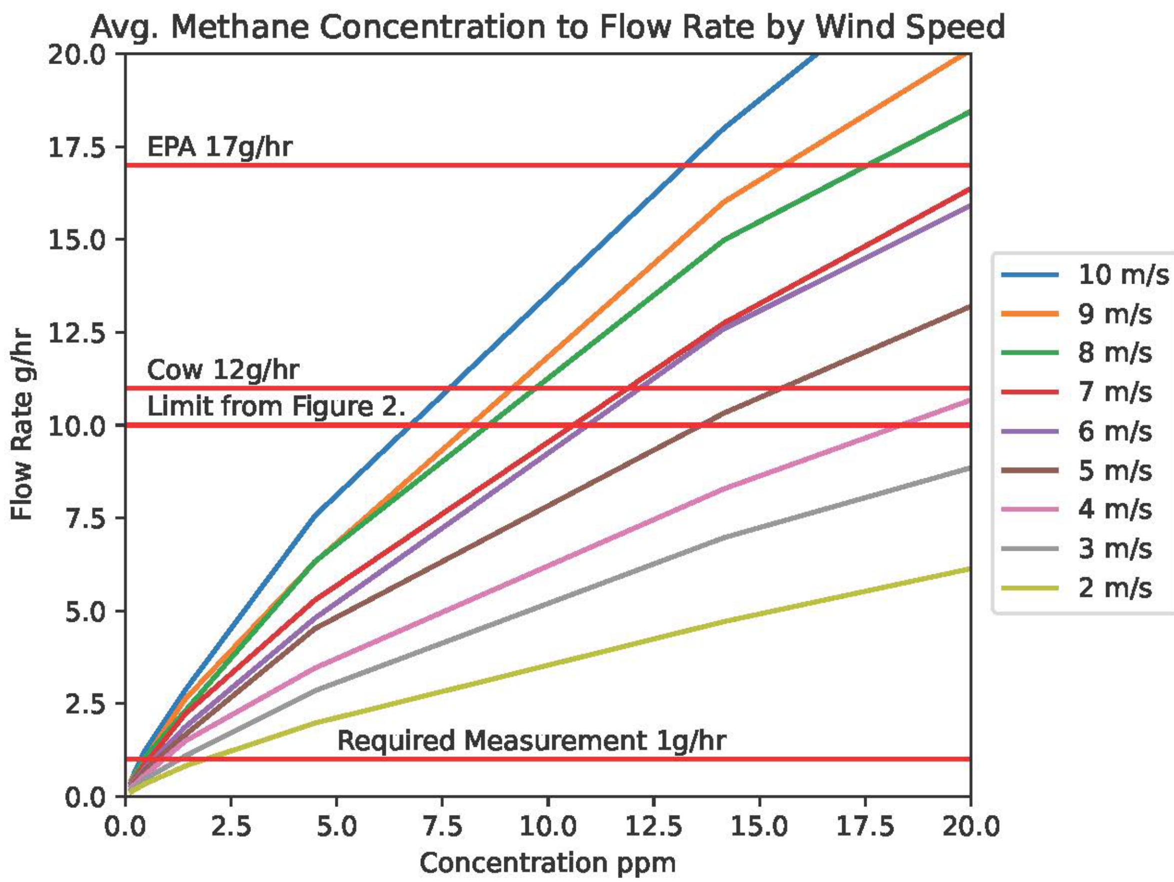

Figure 3: Methane emission flow rates are shown as a function of measured concentration 2m from the source and wind speed. 1 g/hr is the methane reporting requirement for the BIL 2021, EPA 17 g/hr is the limit of detection using OGIs to detect methane leaks.

Figure 3 shows a plot of methane flow rate from a point source in terms of the concentration (as measured 2 m downwind from the point source) and wind speed. This would enable an operator to measure wind speed and methane concentration to estimate the flow rate from an orphan well. This approach would be much less expensive than using a flux tower (for instance) to determine the flow rate since measuring concentration and wind speed is inexpensive. Due to the methods cost, and ease of measurement it could be used as a screening protocol to prioritize wells that merit more investigation before plugging. Generating a figure like Figure 3 requires inverse modeling techniques, which contrasts with the previously described forward modeling techniques.

Our inverse approach accounts for uncertainties including measurement error, uncertainty in the atmospheric conditions, and flow rate from a point source. For this analysis, we used a using a Gaussian dispersion model of a buoyant air plume[4]. We used a standard Bayesian inverse modeling approach with a log-normal prior distribution for the flow rate (with a relatively high expected flow rate) and uniform prior distribution for the stability class. The stability classes considered are classes D, E, and F. This excludes the unstable classes A, B, and C. This implies that measurements should only be collected when the atmospheric conditions are not unstable, which greatly reduces the uncertainty in the estimates of the flow rate. A Markov Chain Monte Carlo (MCMC) approach was used to estimate the distribution of the flow rate given an observation of the concentration and the wind speed. This method can also produce uncertainty bounds (e.g., confidence intervals) for the flow rate.

We are also discussing our simple concentration measurement strategy with O&G well plugging companies (e.g. Curtis Shuck, CEO Welldone Foundation) who are working with several states to quantify orphan well leaks prior to servicing. In the near-term we will provide them with our GPDM analysis, with the caveats to explore faster and cheaper well leak quantification protocols. In the longer-term we propose and plan to conduct small intensity-controlled release experiments to better constrain GPDMs at 0-10 m scales. In parallel we will also perform high resolution plume dispersion simulations using HIGRAD for more rigorous physics based analysis of dispersion, including the development of machine learning algorithms for leak quantification we have done for larger scales for ARPA-E.[3] Sensitivity of atmospheric stability, surface roughness and buoyancy on dispersion of small scales will be assessed. Our systematic fine scale analysis will reduce the uncertainty of source strength intensity by an order of magnitude – by both identifying the operational regime (distance from source, wind conditions) and building a validated and more robust model.

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APPENDIX A

Quantifying Natural Gas Leaks from Oil and Gas Well: Review of Current Methods

About 2.3 million abandoned O&G wells exist and are estimated to emit 200G g CH_4 y^{-1} by EPA/Enverus that implies an average CH_4 leak rate of 10 138 g CH_4 h^{-1} per well.[1] Mean per well emission factors of 0.1 g CH_4 h^{-1}, 3.2 g CH_4 h^{-1}, and 138 g CH_4 h^{-1} for plugged, unplugged and active wells respectively, have been measured, with those abandoned between 1993 and 2015 of 16 g CH_4 h^{-1}.[2] While substantial well to well variability exists in emissions and only a tiny fraction have been sampled, methods to quantify the 1-200 g CH_4 h^{-1} emissions will be key to improve the statistical characterization of leaks. The US government (DOE, DOI) has targeted orphan wells to reduce CH_4 emissions, which demands prioritized, cost effective and reliable operational methods to quantify leaks from individual wells. We evaluate commercial point CH_4 emission quantification techniques using the latest peer review studies and discuss ongoing DOE research on fast, robust, affordable, and operator friendly approaches.

Gas leaks from Oil and Gas wells are typically point sources that can be isolated and quantified by a variety of techniques using in situ CH_4 sniffers (1-8)[3-5] and optical imagers (9)[6].

1. _Static chamber (chamber and CH_4)_; where a container of a known volume (V; m^3) is placed over the emission source, and the change in concentration (C; g m^{-3}) inside the container over time (t; s) is used to calculate the emission (Q; g s^{-1}) as $Q = dC/dt*V$. This is simple and compact and portable with automation feasible (real time CH_4 increase with time versus aliquot sampling for lab analysis). However, potential to exceed the Lower Explosive Limits (LELs) pose a safety hazard that could be addressed using a threshold sensor.

2. _Dynamic chamber (chamber, CH_4 and flow)_; where an additional flow of air is passed through the chamber that together with the source emission results in a stable concentration. The CH_4 flux (Q; g s^{-1}) is calculated from the CH_4 concentration at steady state (C_{eq}; g m^{-3}), the background CH_4 concentration (C_b; g m^{-3}) in the air used to flush the chamber, the height of the chamber (h; m), the flow of air through the chamber (q; m^3 s^{-1}), the footprint of the chamber (a; m^2), and the volume of the chamber (V; m^3) by $Q = ((Ceq-Cb)*h*q*a)/V$. This is preferred as it reduces the likelihood of exceeding LEL inside the chamber.

3. _Bachrach Hi Flow Sampler (CH_4 and flow)_; draws high volumes of air into a measurement chamber at a fixed rate (F; m^3 s^{-1}), and the background CH_4 concentration (X_b; g m^{-3}) and the concentration of CH_4 in the air are measured (X_s, g m^{-3}) and used to calculate the emission rate (Q, g s^{-1}). It draws air at between 226 and 297 L min^{-1} and can measure CH_4 fluxes between 50 g CH_4 h^{-1} and 9 kg CH_4 h^{-1} to an accuracy of ±10 %.

4. _Gaussian Plume Model (ambient CH_4, winds)_: The concentration enhancement of the gas (X; µg m^{-3}), at any point x m downwind of the source, y m laterally from the center

line of the plume, and z m above ground level can be calculated *analytically* from the emission rate (Q; g s^{-1}), the height of the source (h_s; m), and the Pasquill–Gifford stability class (PGSC) as a measure of air stability. Fast sensitive laser based CH_4 sensor (e.g. Picarro, Aeris or Los Gatos) are used to measure the dispersing plume about 2 m above the surface and downwind (1 and 10 m) of the the emission point. Wind speed and wind direction are measured using a weather station or 3-D sonic anemometer. The Gaussian Plume model is recommended for leaks greater 100 g CH_4 hr^{-1} but has been applied to leaks 10 to 80 kg CH_4 hr^{-1} with an uncertainty of ±45 % (Riddick et al., 2019b). Parameters like roughness length, stability and time averages need more systematic evaluation for refinement.

5. *EPA OTM-33a Method (ambient CH_4, winds)*: The concept is based on stationary measurements of CH_4 as a function of the wind direction. It is similar to a Gaussian Plume Model, but instead of moving a detector through a plume, changes in wind direction move the plume across a stationary detector, and thus, the Gaussian plume is formed after taking into account the gas transport. In a recent field campaign, a fast CH_4 analyzer and 3D weather station were set up 20–200 m from the source in the main wind direction and measured for 15 minutes.[4] CH_4 enhancements were averaged as a function of the wind direction in 10° bins. The peak methane mole fraction was determined with a Gaussian fit and used to calculate the methane emission rate $Q=2\pi\cdot\sigma_y\cdot\sigma_z\cdot U\cdot C$

6. *Backward Lagrangian Stochastic Model (ambient CH_4, winds)*: The method uses measurement position, gas concentration, meteorology, and micrometeorology as known inputs, and the model works iteratively backwards to simulate the motion of the air parcel. The model calculates the ratio of downwind concentration to emission, depending on the size and location of the source. The emission rate (Q; g m^{-2} s^{-1}) is then inferred from the measured gas concentration at 1.2 m above ground level (X_m; g m^{-3}) and the background gas concentration (X_b; g m^{-3}) by $Q = (X_m - X_b)/(C/Q)_{sim}$. WindTrax, a commercial inverse dispersion model version, uses wind speed (u; m s^{-1}), wind direction (WD; °), temperature (T; °C), downwind CH_4 concentration (X; µg m^{-3}), location and height of the CH_4 detector, background CH_4 concentration (X_b; µg m^{-3}), the roughness length (z_0; m), and the Pasquill–Gifford stability class for simulation input parameters.

7. *Machine Learning using computational fluid dynamics (CFD) Models (ambient CH_4, winds)*: Recently LANL scientists have developed ML methods trained by high resolution CFD models of plume dispersion and tested them in blind tests for ARPA-E at the METEC site.[5] Using high frequency wind speed, direction and CH4 measurements the method performed very well in locating leaks and also quantifying flux – provided an empirical scale factor attributed to sub-grid model variations was used. In principle this method is an improvement over Gaussian plume, Lagrangian, and OTM-33a and can be implemented in real time, while still accounting for complex micrometeorology.

8. *Eddy Flux Measurements (fast ambient CH_4, winds)*: These are typically performed over large scales for more diffusive leaks and are labor intensive and expensive. Simultaneous high frequency (10Hz) of CH_4 and vertical winds are made and the co-variance of the two gives the upward flux. The fetch of the area sampled is determined by the horizontal winds. Since these winds can vary, the method is not easy for the sampling of fixed point leaks

9. *Quantitative Optical Gas Imaging (QOGI)*: OGI cameras visualize CH_4 leaks plumes emanating from a source using its unique infra-red absorption features. However, their ability to quantify emissions is challenging due to complex signal (path length at distance), complex dispersion and low sensitivity. Recently, a customized QL100 quantification module that uses the image information from a OGI camera and supplementary data (distance from camera to leak source, environmental conditions and gas optical properties) to calculate CH_4 mass emission rate.[6] This new QOGI system is designed for flux quantification and was evaluated using the EPA's Method 21 (CH_4 sniffing values) correlations tables derived by vacuum bagging leaks of several equipment pieces under different service. The test data confirmed that M21 correlations cannot be used to accurately estimate individual leak rates because they are statistical. The QOGI system, on the other hand, was able to provide accurate quantification for individual leaks over the range 1.7 to 1000 g/h. Novel algorithms that analyze the shape of the plume that is determined by the size of the leak and winds can be developed to improve the flux estimation.

The hardware, operational and inversion complexity, performance and capital, labor and software costs that depend on many factors are summarized in the table. Note that the CH_4 sensor costs can range from $1,000 to $100,000 and licensing/development fee for inversion software will need to be estimated. Finally, we stress that CH_4 in gas can range from 99% (dry) to 60% (wet) and sensors will need to account for that. Fortunately, laser based sensors are now available to measure C_2H_6 to do this.

Method/Range	Hardware	Cost	Labor/Model	Safety	Leaks
(1) Static Chamber *0.1-10 g CH_4 h^{-1}*	Chamber CH_4 (real time	$10 K Low (sensor?)	Low/Simple	High Risk (LEL) Engineer-Safe	Simple Sensitive Accurate
(2) Dynamic Chamber *0.1-200 g CH_4 h^{-1}*	Chamber CH_4 sensor Flowrate Q	$25K Mid	Mid/Simple	Safe	Simple Sensitive Accurate
(3-7) Open Air (1-10 m) *10-10,000 g CH_4 h^{-1}*	CH_4 sensor Winds Modeling	$50K Mid-High	Mid/Complex	Safe	Complex Sensitive Uncertain
(9) QOGI (1-10m) *50-10,000 g CH_4 h^{-1}*	OGI-CH_4 Winds Model	$100K High	Low/Complex	Safe	Complex Insensitive Uncertain

Table-A1: A comparison of methods used to measure CH_4 emissions from point O&G well sources

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