Equivalent Leak Definitions for Aerial Methane Imaging LDAR

Abstract

Recent studies have found that gas field emissions come from a fat-tailed distribution, with the bulk of emitted gas coming from a relatively small number of sources. Simultaneously, recent developments in methane detection technology have enabled airborne instruments to remotely survey large areas, although at a lower sensitivity than ground-based devices. Monte Carlo simulations of the detectors and usage protocol allows the determination of aerial methane imaging (AMI) parameters equivalent with current work practice. These parameters can serve as the basis for evaluation of the appropriateness of AMI for regulatory compliance and operational use.

Intro

Reduction of fugitive methane emissions has recently become a more prominent focus of environmental regulatory efforts in North America and elsewhere (US EPA 2015; California Code of Regulations 2017; Colorado Department of Public Health and Environment 2017; Government of Canada 2015; Pennsylvania Department of Environmental Protection 2017). Methane, the primary component of natural gas, has such a high climate warming potential that mitigating its leakage is viewed as an essential part of any climate strategy. However, this mitigation must be cost effective in order to be adopted at scale in the industry.

Leak detection and repair (LDAR) practices are changing rapidly due to two factors: emerging technologies for detection, and a growing consensus that a relatively small number of emission sources are responsible for the bulk of methane emission. These sources, sometimes called "super-emitters," are variously reported to be responsible for 50%-80% of all methane emission (Allen et al. 2013; Brandt et al. 2014; Brandt, Heath, and Cooley 2016; LaCount, Curry, and Russell 2015; Lavoie et al. 2015; Mitchell et al. 2015; Subramanian et al. 2015; Zavala-Araiza, Lyon, Alvarez, Palacios, et al. 2015; Zimmerle et al. 2015). These studies identify a distribution of emission sources with a "fat tail," which is to say a skewed distribution with more extreme values than would be expected from a standard Gaussian distribution. The precise nature of these fat tails is difficult to determine due to their very nature: very large surveys must be performed to get a statistically significant number of large events. Without that significance, the errors in the total emission estimates will be large.

Nevertheless, even without a precise characterization of the shape of the fat tail distribution, the body of current research translates directly into a better strategy for emissions limitation. In particular, the existence of the fat tail implies that the most effective strategy for methane mitigation is to quickly find and fix very large site-level emissions. In this view, an LDAR strategy that made frequent visits, with a higher (i.e. less sensitive) detection threshold, might provide equivalent methane mitigation at a lower cost than a strategy that made occasional visits with a lower threshold. Since it is the total mass of methane emitted that drives the environmental impact, the best strategy will address the largest emitters first.

Aerial methane imaging (AMI) is one emerging technology that could be valuable for quickly finding leaks at the long tail of the distribution. AMI consists of an instrument that flies over the region of interest, remotely sensing and generating images of methane plumes. AMI can be performed from piloted aircraft, helicopters, or drones, at altitudes from 1000 to 10,000 feet above ground level. Academic groups have demonstrated the feasibility of AMI (Thorpe et al. 2017; Frankenberg et al. 2016).

While these results are impressive, some quantitative method is needed to assess whether AMI use as a standard LDAR technique is warranted. The criterion for this decision should be whether the prescribed AMI usage as implemented is as effective as the current work practice in limiting the total mass of methane released into the environment (Epperson et al. 2007). One way to demonstrate the relative effectiveness of the techniques is to realistically simulate both a representative set of gas field leaks, and representative detection technologies, and then to compare the resulting amount of methane detected. An AMI technology combined with usage protocol that achieves equivalent reduction in the simulation is then deemed an equivalent detector.

Methodology

Monte Carlo simulation has been used effectively in the past to establish equivalency for new technologies (Epperson et al. 2007). To establish the equivalency for AMI, we follow a similar approach. Along with the usual simulation requirements (good models of the environment and the detectors), the fat-tailed emission distributions require large numbers of simulations.

FEAST Model

The FEAST model was originally created at Stanford University to model the effectiveness and cost-efficiency of various LDAR technologies (Kemp, Ravikumar, and Brandt 2016). FEAST creates a simulated gas field, creating component-level simulated emissions from suitable random distributions. It then simulates a day-by-day analysis of the field, where leaks may be found via various LDAR techniques or by the simple happenstance of workers visiting the facility for unrelated reasons. Each day, new leaks appear randomly, obeying an underlying base rate. When multiple technologies are simulated, the same set of emissions is presented to each technology for a given realization of the simulation. This provides for faster convergence, which will be important when investigating fat-tailed statistical distributions.

Recently, a version of the FEAST code written in the Python language has been made open-source (Kemp 2017). This code was modified to support different statistical distributions of emissions in gas fields, and a parameterized AMI probability of detection curve.

For our purposes, we simulate two technologies. The baseline standard work product is assumed to be a semi-annual optical gas imager inspection, as required by the current NSPS OOOOa regulations (US EPA 2016). The FEAST model needs to make a few further assumptions not specified in the regulations. Primarily, it needs to assume an observation distance. As many valve components are located on the tops of tanks, an assumption of 10m is appropriate. As described in Kemp, FEAST also makes assumptions about wind conditions based on bootstrap sampling of historical data.

Finally, the null model of serendipitous discovery is included in each technology. Sites are inspected annually, with a 10% probability of leak detection when visited. The assumption is that no dedicated LDAR activity is happening; this represents only the possibility that an emission site is noticed by a site worker without LDAR equipment.

Simulated Field Assumptions

FEAST simulates a gas field with a given number of sites, each of which has a given number of components. The original parameters are drawn from the Fort Worth Natural Gas Air Quality (FWAQS) study (Pring 2017). For this work, the code was extended to permit simulation of lognormal and power-law distributions with arbitrary parameters. The choice of model and model parameters was driven by real-world observations from the scientific literature and discussed below.

In most cases, the literature describes a distribution of leak sizes, and the parameters used to fit that distribution. However, there still remains an overall normalization factor: how many potential leaks were surveyed? For some studies, the survey is a complete survey of a small area, and the number of potential leak sites can be well known. For other studies, especially large area studies, the possible number of leak sizes is much harder to quantify.

For this study, normalizations were computed such that the number of large sources was compatible with observations that roughly 0.5% of sites have substantial leaks (~75 kg/hr, 90 Mscf/day) (Brandt, Heath, and Cooley 2016). Two different underlying distributions were examined, a lognormal distribution and a power-law distribution.

The lognormal model consists of a hybrid model combining FWAQS data with a lognormal distribution as fit by Frankenberg (Frankenberg et al. 2016). This study was performed with AVIRIS-NG, an aerial methane imager and flown over a large area of the Four Corners region. It is quite valuable because its large survey area was sufficient to detect a reasonable number of sources in the fat-tail part of the distribution. Based on the fraction of leaks observed in the FWAQS study, a number of initial leaks is estimated from a Poisson distribution. For each leak, a leak size is assigned via a bootstrap sampling of the FWAQS. For any leak above a certain threshold, that leak size is replaced by a draw from the Frankenberg lognormal distribution. The threshold is chosen to meet the normalization criterion described above.

There are three drawbacks to the Frankenberg lognormal. The first is that the measurements were not specific to oil and gas production sites. Coal mines and natural methane seeps are known to be included in the sample. The sample size of large emissions is too small to meaningfully separate by source, so we must make the assumption that all the emission are drawn from the same statistical distribution. Second, the fit parameters provided by Frankenberg are necessarily biased in the statistical sense. This is due to the fact that a fat tail is always undersampled; it is thus more likely that a larger sample would have resulted in higher lognormal parameters than that it would result in lower parameters. Third, the lognormal does not smoothly join the FWAQS data at the low end. This results in too few leaks at rates just above the limit of the FWAQS, and still below around 10 Mscf/day where the lognormal distribution begins to contribute strongly.

As an alternative, a simple power-law distribution of leaks was also modeled. Power laws are often useful for modeling scale-invariant processes. Choosing a power-law distribution with an index of 1.75 and a cutoff of 100 g/s (430 Mscf/day), and normalizing to the FWAQS at the low end results in a plausible distribution. A series of real-world data sets were tested to see if they were consistent with coming from lognormal distributions (Brandt, Heath, and Cooley 2016); it would be useful to perform a similar analysis with power-law distributions.

Despite the shortcomings in the lognormal estimate, its real-world provenance makes it our preferred leak distribution to simulate.

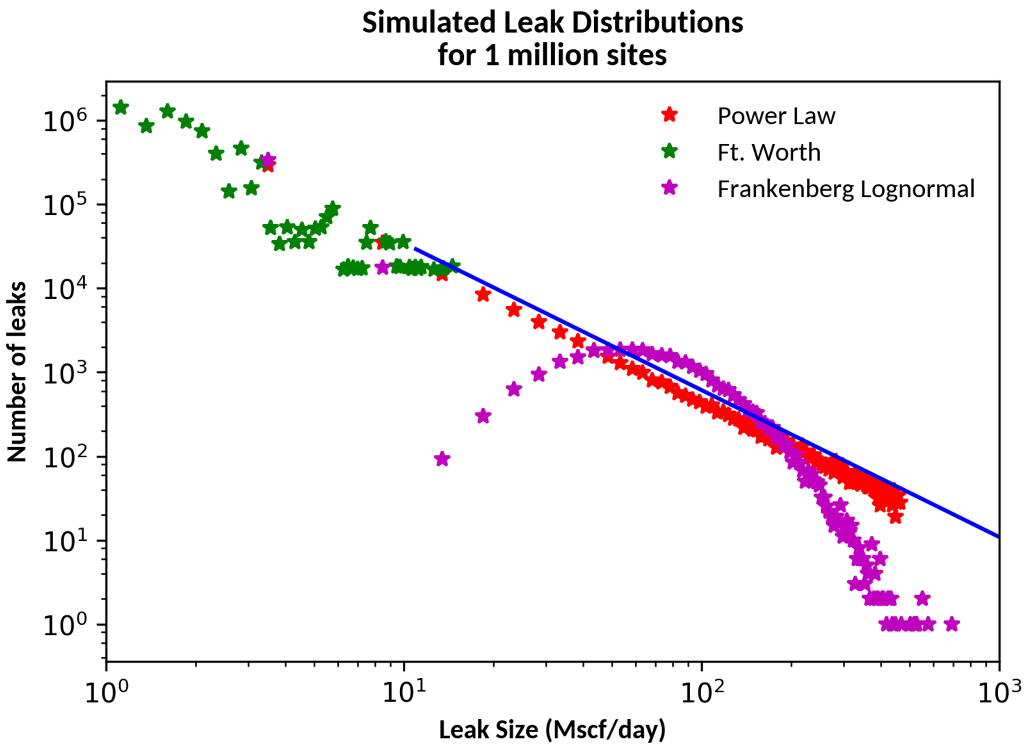

Figure 1: Simulated leak size distributions for 1 million sites

AMI Performance Assumptions

A general aerial methane imager (AMI) was simulated by positing a probability of detection curve. A reasonable general approach is to choose an appropriately scaled error function, parameterized by the emission rate corresponding to a 50% probability of detection, and a width parameter determining the steepness of the probability of detection curve. In order to ensure that the probability of detection goes to zero as the emission rate goes to zero, and exponential with a small scale parameter is applied as well.

The parameterized probability of detection curve is thus expressed:

$$P_d(x \mid \mu, w, s) = e^{-\frac{x}{s}}\left(\frac{1}{2} + \frac{1}{2}\operatorname{erf}\left(\frac{x-\mu}{w}\right)\right)$$

where erf is the standard error function. Probability of detection curves for various parameters are shown in **Error! Reference source not found.**.

Simulations were run for a variety of center values μ ranging from 20 Mscf/day to 150 Mscf/day. To reduce the dimensionality of the problem, the width value *w* was always taken to be 60% of μ.

A distinct advantage of AMI is the ability to revisit sites more frequently, due to the simplicity of deployment and lower cost. To explore the performance sensitivity to this parameter, simulations were run at a variety of survey intervals ranging from 7 days to 90 days.

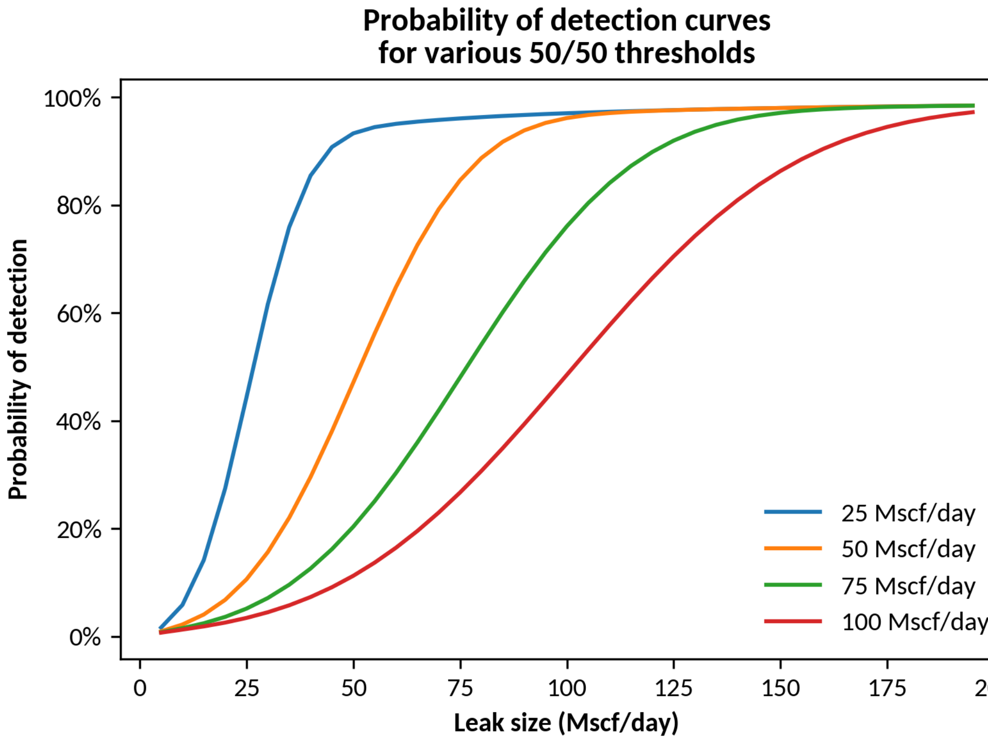

Figure 2: AMI probability of detection as a function of leak size, for a variety of center threshold values.

Results

Monte Carlo simulations were performed to compare the performance of AMI to OGI for a variety of AMI parameters. For each point in the AMI configuration space (that is, AMI probability of detection parameters and survey interval), a large number (usually 30,000) sites were simulated for 10 years. Figure 3 shows the relative performance of an AMI device to the OGI baseline. Relative performance means the ratio of the total methane mass loss prevented by the AMI to the total methane mass loss prevented by the OGI. Values greater than 100% thus indicate that an AMI with the given sensitivity (left axis) and survey interval (bottom axis) would outperform the baseline OGI.

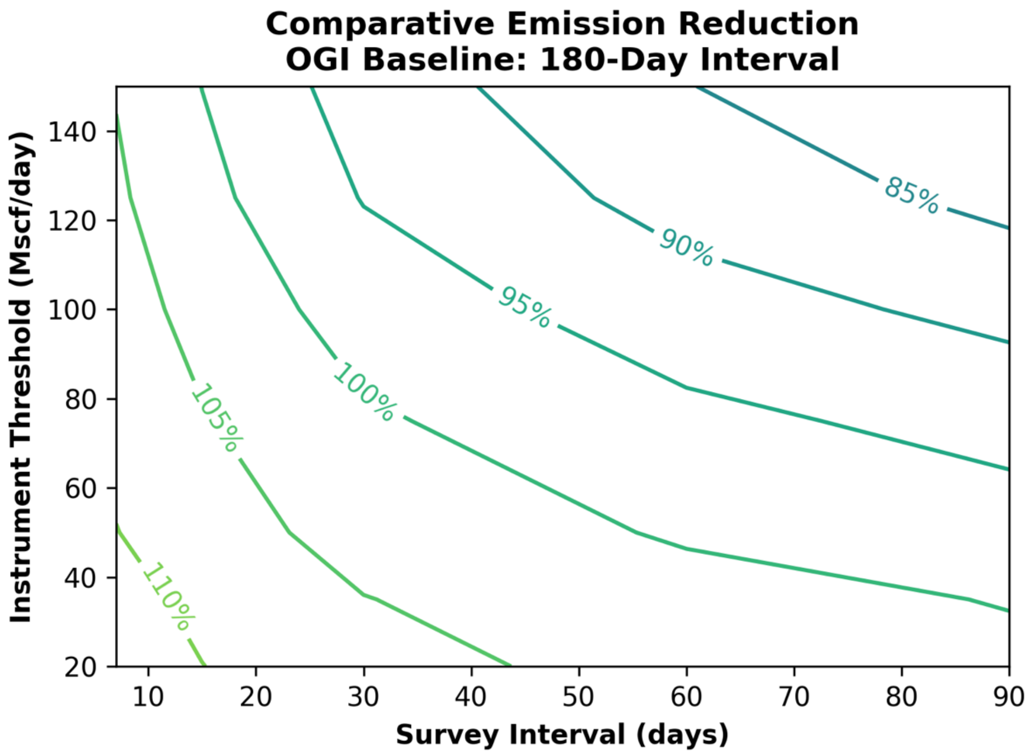

Figure 3: AMI performance relative to OGI baseline (semi-annual inspections from 10m) for a lognormal distribution of fugitive emissions. "Instrument threshold" indicates the leak rate at which 50% of emission sites are detected. Above 100% indicates that the AMI is more effective than the OGI at preventing methane loss. The 100% contour represents the set of AMI thresholds and survey intervals that are result in equivalent emission prevention as compared to the regulatory baseline OGI.

The result is immediately useful for establishing equivalence of aerial methane imaging with the regulatory standard of OGI. Any combination of instrument sensitivity and survey interval that lies along the 100% contour is equivalent to OGI. For example, from Figure 3 we can see that an instrument with a 50/50 detection threshold of 80 Mscf/day used monthly would prevent an equivalent amount of methane emission as semi-annual OGI inspections.

Some jurisdictions may require more frequent OGI inspections. Comparisons of AMI to OGI inspections every 90 or 120 days are shown in Figure 4. As expected, more frequent OGI baselines require more aggressive AMI in order to establish equivalency.

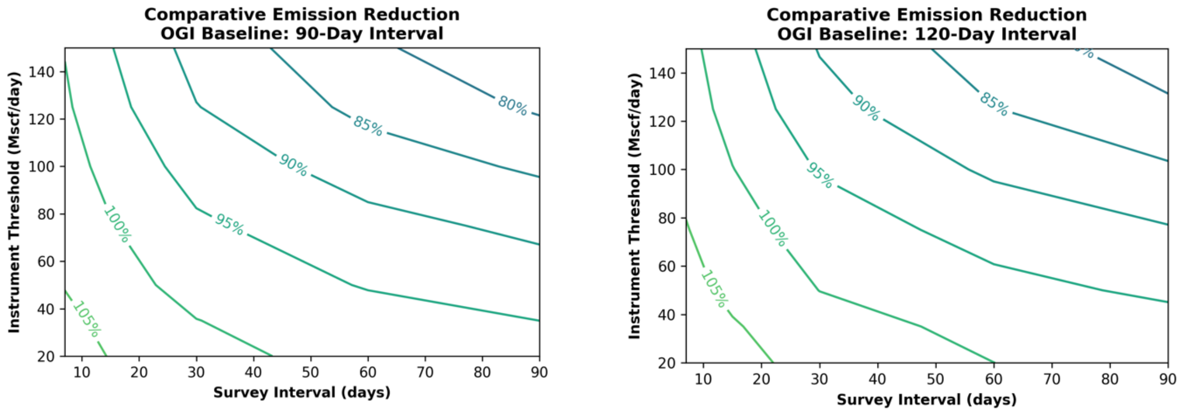

Figure 4: AMI performance relative to alternative OGI baselines. Left figure shows AMI against OGI performed every 90 days at 10m; right figure is at 120 days at 10m.

Discussion

Comparison of field models with measured data

It is illustrative to compare the distributions of simulated leaks generated with the data that has been collected from actual oil & gas emissions. That data is limited and incomplete, so it cannot serve as a proper validation of the simulation model. However, we can examine it for consistency.

Frankenberg, *et al.* (Frankenberg et al. 2016) fit a lognormal distribution based on 245 sources detected in the Four Corners region. This data set contains not only oil & gas operational sites, but also coal mines and naturally occurring emission. Nevertheless, the large area surveyed probed a portion of the extreme-value tail of the source distribution. They were able to calculate fit parameters for the lognormal distribution, as well as some confidence intervals. Their most-likely parameters were also the high end of their confidence interval, because they necessarily have undersampled the true population of the largest emitters. The mode of the distribution is approximately 70 Mscf/day.

Zavala-Araiza, *et al.* (Zavala-Araiza, Lyon, Alvarez, Davis, et al. 2015) provide a plausible theoretical basis for expecting leak sizes to be lognormally distributed. However, Brandt, Heath, and Cooley (Brandt, Heath, and Cooley 2016) examine ~15,000 measurements from 18 different studies on leaks ranging from individual components to site-level facilities. They attempt to find a lognormal distribution consistent with all the measurements. However, they make two important findings. First, the “best-fit” lognormal for each dataset systematically underpredicts the fat tail of the distribution, suggesting that the lognormal may not be an appropriate aggregate distribution to use. Second, pairwise Kolmogorov-Smirnov tests show that almost none of the datasets share an underlying parent distribution with another.

The power-law distribution has fewer emission sites in the range of 40 to 200 Mscf/day, but more leaks at the more extremes. However, it is arbitrarily cut off at 100 g/s (464 Mscf/day) in the simulation, so there are no leaks larger than that. Table 1 shows the fraction of simulated well sites larger with leaks larger than a given rate.

Leak Distribution	Leaks >25 Mscf/day	Leaks >50 Mcsf/day	Leaks > 100 M	Leaks > 200M
Lognormal	3.4%	2.6%	1.0%	0.1%
Power law	2.9%	1.6%	0.8%	0.3%

Table 1: Fraction of simulated leaks above various leak rates. The lognormal distribution has more leaks at moderately large leak rates, while the power law has more leaks at the largest rates.

Conclusion

Monte Carlo simulations based on the open-source FEAST model were used to generate equivalency contours for aerial methane imaging, as compared to the standard OGI practice outlined in the potential OOOOa regulations. The contours describe the set of AMI sensitivities and survey intervals needed to prevent the same amount of methane emissions as the standard practice.

For regulatory purposes, the goal is to limit the total amount of emitted methane. Thus, alternative work practices that limit methane emission to the same degree as the standard work practice should be considered for compliance. These simulations provide a basis for establishing the AMI operational parameters that would achieve that methane limitation. Such alternative work practices may have additional benefits, including reduced cost or improved worker safety, that would make them a preferred choice for oil and gas LDAR.

Bibliography

Allen, David T., Vincent M. Torres, James Thomas, David W. Sullivan, Matthew Harrison, Al Hendler, Scott C. Herndon, et al. 2013. “Measurements of Methane Emissions at Natural Gas Production Sites in the United States.” *Proceedings of the National Academy of Sciences* 110 (44): 17768–73. doi:10.1073/pnas.1304880110.

Brandt, Adam R., G. A. Heath, E. A. Kort, F. O’Sullivan, G. Pétron, S. M. Jordaan, P. Tans, et al. 2014. “Methane Leaks from North American Natural Gas Systems.” *Science* 343 (6172): 733–35. doi:10.1126/science.1247045.

Brandt, Adam R., Garvin A. Heath, and Daniel Cooley. 2016. “Methane Leaks from Natural Gas Systems Follow Extreme Distributions.” *Environmental Science & Technology* 50 (22): 12512–20. doi:10.1021/acs.est.6b04303.

California Code of Regulations. 2017. “Greenhouse Gas Emission Standards for Crude Oil and Natural Gas Facilities.” Accessed June 22. https://www.arb.ca.gov/regact/2016/oilandgas2016/oilgasfro.pdf.

Colorado Department of Public Health and Environment. 2017. “Colorado Regulation #7.” *Control of Ozone via Ozone Precursors and Control of Hydrocarbons via Oil and Gas Emissions*. Accessed June 22. https://www.colorado.gov/pacific/sites/default/files/5-CCR-1001-9_1.pdf.

Epperson, David, Miriam Lev-On, Hal Taback, Jeffrey Siegell, and Karin Ritter. 2007. “Equivalent Leak Definitions for Smart LDAR (Leak Detection and Repair) When Using Optical Imaging Technology.” *Journal of the Air & Waste Management Association (1995)* 57 (9): 1050–60.

Frankenberg, Christian, Andrew K. Thorpe, David R. Thompson, Glynn Hulley, Eric Adam Kort, Nick Vance, Jakob Borchardt, et al. 2016. “Airborne Methane Remote Measurements Reveal Heavy-

Tail Flux Distribution in Four Corners Region." *Proceedings of the National Academy of Sciences* 113 (35): 9734–39. doi:10.1073/pnas.1605617113.

Government of Canada, Environment Canada. 2015. "Regulations Respecting Reduction in the Release of Methane and Certain Volatile Organic Compounds (Upstream Oil and Gas Sector) - Proposed Regulations - Regulations and Other Instruments - CEPA Environmental Registry - Acts & Regulations." July 9. http://www.ec.gc.ca/lcpe-cepa/eng/regulations/detailReg.cfm?intReg=243.

Kemp, Chandler E. (2017) 2017. *FEAST: Fugitive Emissions Abatement Simulation Testbed*. Jupyter Notebook. EAO Group at Stanford University. https://github.com/EAOgroup/FEAST.

Kemp, Chandler E., Arvind P. Ravikumar, and Adam R. Brandt. 2016. "Comparing Natural Gas Leakage Detection Technologies Using an Open-Source 'Virtual Gas Field' Simulator." *Environmental Science & Technology* 50 (8): 4546–53. doi:10.1021/acs.est.5b06068.

LaCount, Robert, Thomas Curry, and Clement Russell. 2015. "Methane Emissions in the Natural Gas Life Cycle." http://mjbradley.com/sites/default/files/MJBradleyWIEBNGMethaneEmissionsImplicationsforPolicymakersFinal.pdf.

Lavoie, Tegan N., Paul B. Shepson, Maria O. L. Cambaliza, Brian H. Stirm, Anna Karion, Colm Sweeney, Tara I. Yacovitch, Scott C. Herndon, Xin Lan, and David Lyon. 2015. "Aircraft-Based Measurements of Point Source Methane Emissions in the Barnett Shale Basin." *Environmental Science & Technology* 49 (13): 7904–13. doi:10.1021/acs.est.5b00410.

Mitchell, Austin L., Daniel S. Tkacik, Joseph R. Roscioli, Scott C. Herndon, Tara I. Yacovitch, David M. Martinez, Timothy L. Vaughn, et al. 2015. "Measurements of Methane Emissions from Natural Gas Gathering Facilities and Processing Plants: Measurement Results." *Environmental Science & Technology* 49 (5): 3219–27. doi:10.1021/es5052809.

Pennsylvania Department of Environmental Protection. 2017. "Draft GP-5 and GP-5a and Supporting Documents." March 13. http://www.elibrary.dep.state.pa.us/dsweb/View/Collection-13330.

Pring, Michael. 2017. "Fort Worth Natural Gas Air Quality Study." Accessed May 5. https://www3.epa.gov/ttnchie1/conference/ei20/session6/mpring.pdf.

Subramanian, R., Laurie L. Williams, Timothy L. Vaughn, Daniel Zimmerle, Joseph R. Roscioli, Scott C. Herndon, Tara I. Yacovitch, et al. 2015. "Methane Emissions from Natural Gas Compressor Stations in the Transmission and Storage Sector: Measurements and Comparisons with the EPA Greenhouse Gas Reporting Program Protocol." *Environmental Science & Technology* 49 (5): 3252–61. doi:10.1021/es5060258.

Thorpe, A. K., C. Frankenberg, D. R. Thompson, R. M. Duren, A. D. Aubrey, B. B. Bue, R. O. Green, et al. 2017. "Airborne DOAS Retrievals of Methane, Carbon Dioxide, and Water Vapor Concentrations at High Spatial Resolution: Application to AVIRIS-NG." *Atmos. Meas. Tech. Discuss.* 2017 (May): 1–23. doi:10.5194/amt-2017-51.

US EPA. 2015. *E-CFR: Title 40: Protection of Environment PART 60—STANDARDS OF PERFORMANCE FOR NEW STATIONARY SOURCES (CONTINUED)*. *Electronic Code of Federal Regulations*. Vol. Title 40: Protection of Environment PART 60—STANDARDS OF PERFORMANCE FOR NEW STATIONARY SOURCES (CONTINUED). https://www.ecfr.gov/cgi-bin/retrieveECFR?gp=1&SID=09508383c72f67779fa20ffddfbe8396&ty=HTML&h=L&mc=true&r=SUBPART&n=sp40.8.60.oooo_0a.

US EPA, OAR. 2016. "New Source Performance Standards and Permitting Requirements." Overviews and Factsheets. *US EPA*. September 27. https://www.epa.gov/controlling-air-pollution-oil-and-natural-gas-industry/new-source-performance-standards-and.

Zavala-Araiza, Daniel, David Lyon, Ramón A. Alvarez, Virginia Palacios, Robert Harriss, Xin Lan, Robert Talbot, and Steven P. Hamburg. 2015. "Toward a Functional Definition of Methane Super-

Emitters: Application to Natural Gas Production Sites." *Environmental Science & Technology* 49 (13): 8167–74. doi:10.1021/acs.est.5b00133.

Zavala-Araiza, Daniel, David R. Lyon, Ramón A. Alvarez, Kenneth J. Davis, Robert Harriss, Scott C. Herndon, Anna Karion, et al. 2015. "Reconciling Divergent Estimates of Oil and Gas Methane Emissions." *Proceedings of the National Academy of Sciences* 112 (51): 15597–602. doi:10.1073/pnas.1522126112.

Zimmerle, Daniel J., Laurie L. Williams, Timothy L. Vaughn, Casey Quinn, R. Subramanian, Gerald P. Duggan, Bryan Willson, et al. 2015. "Methane Emissions from the Natural Gas Transmission and Storage System in the United States." *Environmental Science & Technology* 49 (15): 9374–83. doi:10.1021/acs.est.5b01669.