WHITE PAPER

Evaluation of Emerging Methane Detection Methods

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CLARIFICATION:

This revised version of the white paper clarifies that all modeled emissions mitigation and cost scenarios within the paper are based on hypothetical representations of operationalizing detection techniques. These revisions emphasize the purpose of the white paper, which is to represent and model potential ranges of deployment program options based on measurement data and qualitative operational information provided by oil and gas operators. Hypothetical combinations of technologies, sampling frequency, costs presented in the modeling portion of the paper do not specifically correspond to actual usage of currently commercially available technologies.

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Executive Summary

Methane, a potent greenhouse gas, can warm the atmosphere 28–86 times as fast as carbon dioxide. Understanding how to effectively measure and reduce methane emissions is a top priority for stakeholders across the natural gas value chain, especially in light of net-zero commitments of governments and organizations around the world. To succeed, stakeholders need access to consistent and effective detection methods for methane emissions—especially as regulators, including the U.S. Environmental Protection Agency (EPA), explore rulemaking on various detection methods.

EPA has released draft new source performance standards for new, restructured, and modified sources, along with guidelines for reducing methane emissions from existing sources. EPA is currently seeking information to support the use of advanced methane detection technologies for compliance with the proposed regulations. The purpose of this white paper is to provide information on the technological capabilities and costs of the various detection technologies and is based in part on a data set provided by oil and gas companies to GTI.

GTI, the Environmental Defense Fund (EDF), Highwood Emissions Management, and several production companies collaborated to study leak detection and repair (LDAR) technologies and identify information related to the efficacy of the various detection technologies. This study—conducted by GTI and funded by EDF—intends to evaluate the performance and cost effectiveness of emerging methane detection technologies informed in part by real-world data. It also aims to help provide insight into understanding limitations and difficulties with operationalizing these programs.

This report summarizes the data that was generously contributed to the program by seven different organizations, then aggregated. The data collected can be classified into broad categories that include handheld, mobile/vehicle based, aerial-based, continuous monitoring (CM), and satellite-based. During the study, it became clear that there were insufficient data regarding the cost of programs, so simulations of real-world scenarios were run to estimate cost ranges using LDAR-Sim. Additional simulations were deployed—namely to evaluate the effectiveness of more frequent surveys. The LDAR programs detailed and simulated in this report represent *case studies* and are not immutable representations of any given technology or technology class.

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Key Findings

- While hundreds of data files were shared with GTI containing hundreds of thousands of data points, it is important to note that each technology:

  – Operates according to very different sensing principles,

  – Is deployed using different work practices,

  – Employs different analytics to estimate source location and emission rates, and

  – Reports different information to the end user.

  There are no data-reporting standards for these technologies, so for the purposes of the study, GTI focused on hypothetical use cases to explore the performance of advanced methane detection technologies.
- Work practices impact detection, so identical technologies deployed with different work practices can mitigate varying amounts of methane with differing costs. This underscores the need for data and reporting standards to streamline the collection, dissemination, and comparison of emissions data from different technologies.
- The performance of various technologies depends on the conditions under which they operate. Importantly, every methane detection technology resulted in emissions reductions with varying effectiveness and cost.
- Continuous monitoring (CM) sensors demonstrated the highest potential reduction in emissions—but cost relatively more in terms of mitigating methane in U.S. dollars per metric ton of mitigated carbon dioxide equivalent of fugitive methane ($/tCO_2e$).
- CM data has great potential for exploring long-term trends in emissions for an individual sites. However, there will be an initial learning curve to determine site operating parameters, to optimize sensor placement (height and orientation), and emissions characteristics for each site to properly operationalize data and avoid false-positive deployments.
- A time series or histogram of CM data shows highly variable emission rates, since the system or systems measure emissions across the entire site. Several conclusions can be drawn, and this type of data necessitates a follow-up investigation through examination of SCADA data or by ground crews at the appropriate times to locate the emission source. Nevertheless, this data can be very useful in avoiding major losses for the operator and averting major leaks.
- Aircraft-based technologies had the lowest cost per ton to mitigate emissions but were capable of mitigating the smallest percentage of emissions by focusing only on large, high-value sources. More sensitive technologies tend to be more expensive—because instrumentation must be more precise and/or because work practice requires more meticulous attention to smaller leaks; these mitigate more emissions but at a relatively higher cost, on average.
- The research shows a varied range of emissions reduction where a sensitive CM sensor combined with aggressive follow-up work practices is the most effective at identifying and mitigating emissions.

As regulators and operators consider advanced methane detection technologies, the need for data and reporting standards should remain top of mind; without them, it is difficult to make comparisons across sites and instead require a site-by-site approach for measuring the effectiveness of emissions reductions and cost.

Introduction

EPA has released draft new source performance standards for new, restructured, and modified sources along with guidelines for reducing methane and volatile organic emissions from existing sources. The proposed standards give owners/operators the opportunity to use advanced methane detection technologies to find and repair major emissions at well sites and compressor stations. EPA is currently seeking information to support the use of advanced methane detection technologies for this approach. The purpose of this white paper is to inform decisions on the capabilities and costs of the various detection methodologies and is based in part on a data set provided by oil and gas companies to GTI.

Methane emission detection and quantification methodologies have advanced greatly since the beginning of the DOE ARPA-E Methane Observation Networks with Innovative Technology to Obtain Reductions (MONITOR) program in late 2014. The MONITOR program, coupled with the increased understanding that more methane was possibly leaking from oil and gas operations than previously thought, sparked considerable advancement of innovation in detection and quantification methodologies. As such, several of these new detection platforms have been deployed as more companies across the natural gas supply chain place a greater focus on reducing emissions.

The deployed detection platforms can be classified into broad categories: handheld, mobile/vehicle-based, aerial-based, fixed/continuous monitoring (CM), and satellite-based. These broad categories can be further divided to be more representative of the types of data that are collected. For instance, the handheld technologies are the more traditional leak detection and repair (LDAR) technologies that satisfy current regulatory requirements and can be broken down into EPA Method 21 devices or EPA Optical Gas Imaging (OGI) devices.

Mobile/vehicle-based detection systems include mobile labs and/or advanced mobile leak detection systems (no data in GTI database). Aerial-based techniques can include both manned (fixed-wing, helicopter) and unmanned platforms (drones, unmanned aerial platforms). Within the manned aerial platforms, there is a range of philosophies for the technologies and survey methodologies that, when combined, can affect survey speed and minimum detection limit (MDL). Some aerial technologies/methods elect to fly higher and faster and/or use a technology with a lower sensitivity to cover more sites in a day. While other aerial remote sensing technologies/methodologies may fly lower and slower and/or use a technology with a higher sensitivity to cover fewer sites in a day. This white paper will focus on a spectrum of these technologies. Several technologies were represented in the GTI dataset, and were used to inform hypothetical technologies/methodologies to explore the tradeoff of sensitivity versus speed (i.e., cost per site). Other aerial technologies can use an aerial mass balance approach encompassing a site or area. In terms of drone technologies, current Federal Aviation Administration (FAA) regulations require that the drone be operated within visual line of sight (VLOS). This requirement means that the drone must be driven to each site that is scanned.

Continuous monitoring (CM) is growing in popularity as it can rapidly identify new leaks. Some CM solutions regularly scan an entire site or use a laser detector to monitor a large area of the site for emissions. These systems can usually be deployed in smaller numbers per site. Other continuous monitors use “point” sensors to monitor a single location at the site. For some sensors to detect a leak, the emission plume must be carried via the wind to the location of the sensor; therefore, must be deployed in larger numbers. For the purposes of this paper, GTI evaluated hypothetical scenarios that were informed by data, qualitatively reported information, and surveyed responses from operators that included various ranges of quantitative information to estimate conservative and more aggressive monitoring approaches with respect to work practices. The different scenarios are described as CM_WP_1 and CM_WP_2 to incorporate a variety of techniques in operations, frequency of addressing leaks, and deployment methodologies. CM_WP_1 represents continuous monitoring systems that have lower startup and operating costs, but are of lower sensitivity and therefore require less frequent close-range follow-up. The trade-off is that fewer alerts lead to lower mitigation but at a lower cost because follow-up can be expensive. CM_WP_2 represents continuous monitoring systems that have higher startup and operating costs, but also more frequent mitigative activities at lower MDLs meaning that more overall emissions can be mitigated.

The intention of the spectrum of simulations that include varied frequencies, detection limits, operational practices, and technology types is to illustrate the variety of business practices and deployment patterns that may be required to operationalize various technologies. The scenarios and parameters used for the purposes of modeling are not representative of any currently available commercial technology, and are instead a representation of a potential bounds of CM work practices (WP).

The central factor to understanding, managing, and maximizing reductions of emissions is the proper deployment of all platforms and then operationalizing the information collected. Companies, particularly in the natural gas production segment, have begun deploying these technologies and compiling a wealth of knowledge about the emissions from their own assets.

To begin to take advantage of the wealth of information, a collaboration has begun between the Gas Technology Institute, the Environmental Defense Fund, and several production companies. The purpose of this collaborative effort is to begin to publicly share information that the production companies have collected to understand what information more clearly can be gathered with these new technologies. Furthermore, the data provided can be used to determine limitations and difficulties with operationalizing the information collected. GTI acted as a repository for the information and the data received has been summarized in this paper. It will not be published publicly due to the challenges of anonymizing the sources appropriately.

The data and cost information discussed in this white paper can be used as specific case studies of the various detection methodologies available and the type of information that can be collected from the various platforms. In addition, the paper will describe examples of detailed modeled cost information, informed by the data provided by the companies, on a dollar per ton of abatable CO_2 equivalent (CO_2e) basis across the measurement platforms[1].

1 The value used in this report for Global Warming Potential of methane (CH4) was 28.

Collected Emissions Data

To date, seven entities have contributed data from the Permian basin to the GTI database, along with one small dataset from the Bakken. They are identified by the first seven letters of the alphabet (A through G) as shown in Table 1. The submitted data contained hundreds of files, however only 29 files contained raw or summarized data, while many of the other files contained explanatory information detailing the detected emissions. The files contained information from eight detection methodologies including two types of continuous monitoring systems, three types of aerial systems, a drone-based system, and a satellite-based system. In total, we received hundreds of thousands of data points, the majority of which did not contain leak indications. Table 1 summarizes the data at a high level, detailing whether each technology can detect that a leak has occurred, whether it can provide guidance on the location of the leak, and whether it can provide an emission rate. Further, Table 1 indicates the minimum detected emission reported in the data set with each technology. It is important to note that the minimum reported emission in Table 1 only indicates the lowest emission rate reported in that particular set of data. It does not indicate the technology MDLs. Also, the data does not include reported uncertainty for any of the reported emissions in the data.

Table 1. Summary table of data received. All data is in the Permian unless otherwise noted.

Company	Anonymized Technology	Emitting Equipment Identified?	Lowest Reported Emission Rate in the Dataset (kg/hr)
A	CM_1	No	0.01
A	Satellite	No	524.5
A	Aerial_1	No	63.6
A	Drone	Yes	N/A
B	Aerial_3	Yes	2.8
B	Aerial_1	Yes	27.2
B	Aerial_3 Bakken	Yes	53
B	CM_1	No	10
B	CM_3	Yes	0.2
C	Aerial_3	Yes	2.8
C	Aerial_1	Yes	56.8
C	Aerial_2	Yes	3.2
C	Drone	No	N/A
D	Aerial_3	Yes	2.8
D	CM_1	Yes	0.01
E	Aerial_3	Yes	7.4
F	CM_3	Yes	0.02
G	CM_2	Yes	N/A

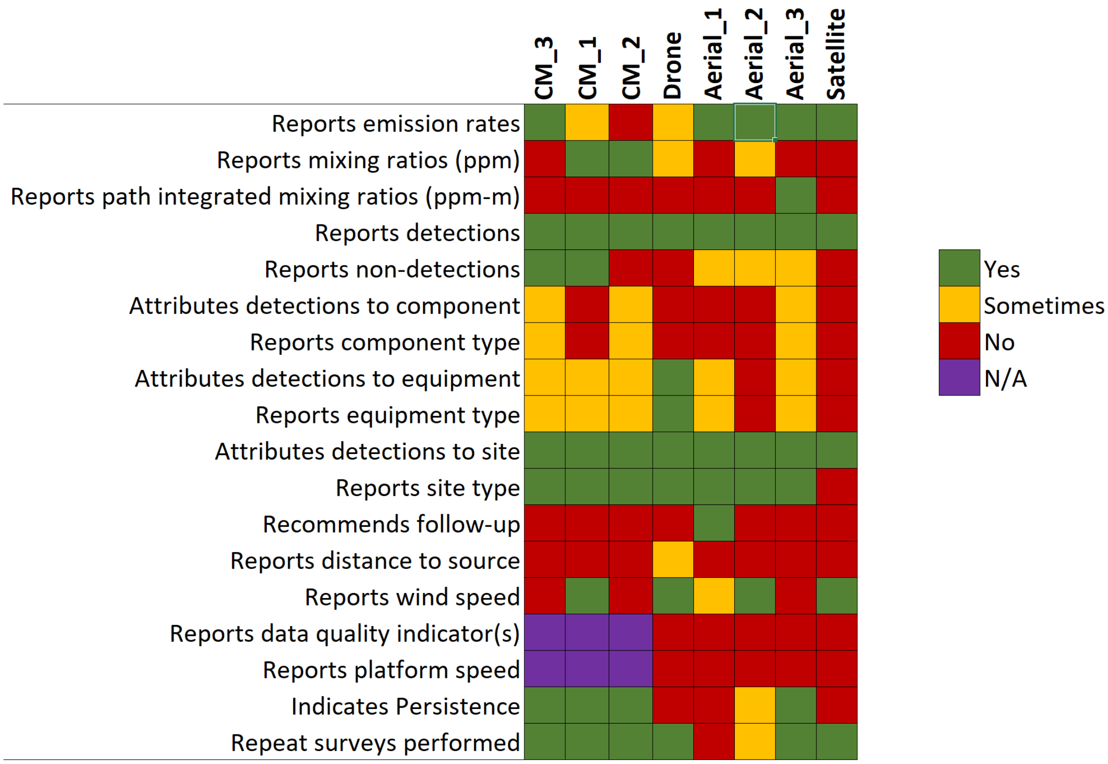

Figure 1. Qualitative Summary of the Technologies in the Data Set

The methodologies present in the GTI dataset can be evaluated qualitatively at a high level as shown in Figure 1. Each of the platform types has separate capabilities, which can evolve over time as many of the products are undergoing active development. The qualitative assessment shown in Figure 1 is intended to capture the current state of the methodologies that is in the dataset.

Figure 1 illustrates the marked variability that exists in the characteristics of the data and information products derived from each of the detection methodologies present in the collected GTI dataset and are the targeted focus of this report. Each methodology operates according to very different sensing principles, is deployed using different work practices, employs different analytics to estimate source location and emission rates, and reports different information to the end user. Since work practices impact detection, this means that identical technologies deployed with different work practices can mitigate varying amounts of methane and differing costs. Spatial scale of measurement varies considerably from methodologies that can narrow in on individual pieces of equipment to those that only acquire a single measurement for an entire facility. Whether a methodology reports 'non-detections' is a critical piece of information that is often unavailable and makes it difficult to determine the proportion of sites at which detections occur. Figure 1 highlights the need for data and reporting standards to streamline the collection, dissemination, and comparison of emissions data from the different technologies. The lack of these standards therefore mean that the findings of this report apply only to the hypothetical cases modeled.

Summary of Collected Data

As mentioned previously, GTI has assembled a dataset containing information from several different detection platforms. In the following sections, we detail some of the ways in which the data can be used to explore the performance of advanced methane detection methodologies shown in Figure 2.

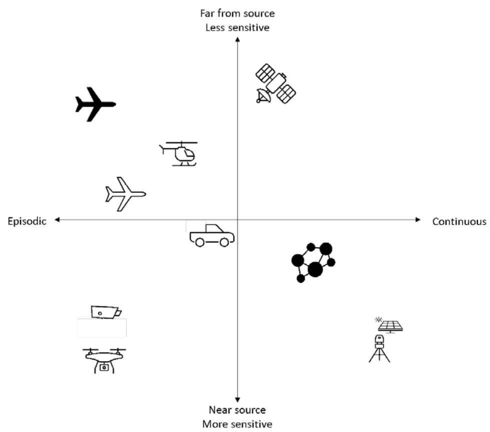

Figure 2. Methane detection technology ecosystem

Aerial Remote Sensing

Aerial remote sensing technologies vary, some generally fly at a higher altitude and faster speeds, therefore are focused on finding only the largest emission sources; others fly at lower altitudes and slower speeds so do not cover as much ground each day. GTI acquired both types of data, most of which represented the latter category. In all, information from 25 emission detections at higher altitutes were provided. Key information included with the data that was provided to GTI but not released publicly shows images of the sites and locations of the emissions.

The lower altitude data was the most heavily represented aerial remote sensing data in the GTI collected data set with four companies providing data and two of those companies providing multiple data sets across years and locations. Figure 3 shows the distribution of emission sources across all of the data in the data set, revealing similarities to the other data sets with 65% of the emissions coming from approximately 90 of the nearly 750 emissions identified (12% of sites).

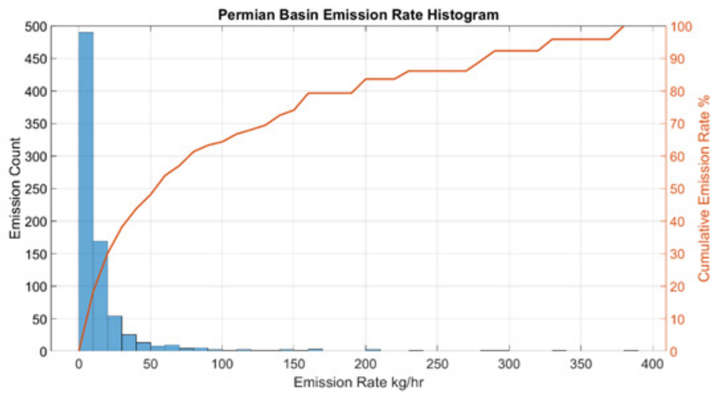

Figure 3. Histogram of all emission sources provided using low-altitude aerial remote sensing technology.

From the data received, most types of aerial technologies provide additional imaging of the emission sources as shown in Figure 4. The colors have been altered in the figure to anonymize the location.

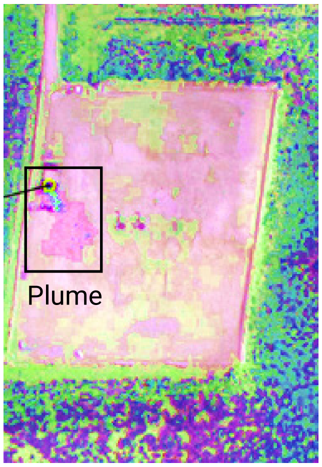

Figure 4. Example detection image provided along with the detection information shared in the data set

Continuous Monitoring

The most extensive portion of the dataset was obtained from CM methodologies due to large numbers of data points each sensor collects. These systems can include multiple sensors placed around the site to wait for a methane plume to be carried on the wind to the location of the sensor. The systems measure high frequency concentration data (e.g., 1 Hz) and report the data on an aggregated/time averaged basis, ranging between 1 and 60 minutes. The CM portion of the dataset contains data from three vendors.

Interpreting CM data can be nuanced due to the potential for emissions to be intermittent and the possibility for changing wind speeds and directions. For example, Figure 5 shows the distribution of emission detections for a 91-hour period for one site. Examining the histogram of the data shows a skewed distribution of emissions at varying rates over the 91-hour period, with a few larger emission rate detections driving the overall emissions. However, examining the raw sensor data shows a slightly different potential story.

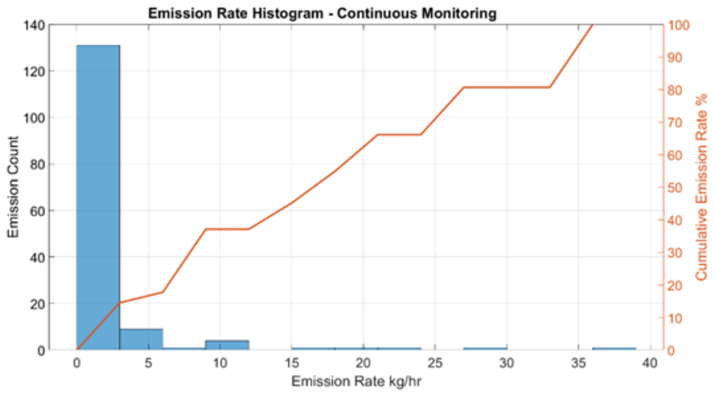

Figure 5. Emission rate histogram for a 91-hour period for a CM monitor at a single site

Figure 6 shows the raw time series data of emission rate, wind speed, and methane concentration while for the same 91-hour period of data shown in Figure 5. Looking at the raw time series reveals that some interpretation is needed for the data collected at the site. First, all detections presented in the histogram in Figure 5 may be from the same source and only appear to be separate due to changing wind speeds and directions. Also, the raw data in Figure 6 does not fully identify whether the leak is persistent (continuously emitting, usually associated with fugitive emissions) or intermittent (starts and stops emitting, usually associated with the engineered emissions). Continuous monitoring data has great potential for exploring long-term trends in emissions for an individual site. However, there will be an initial learning curve to determine site operating parameters, to optimize sensors placement (height and orientation), and emissions characteristics for each site to properly operationalize data and avoid false-positive deployments.

Figure 6. An example time series of methane emission rate, methane concentration, and wind speed from a single CM_WP_1 monitor at one site over 91 hours.

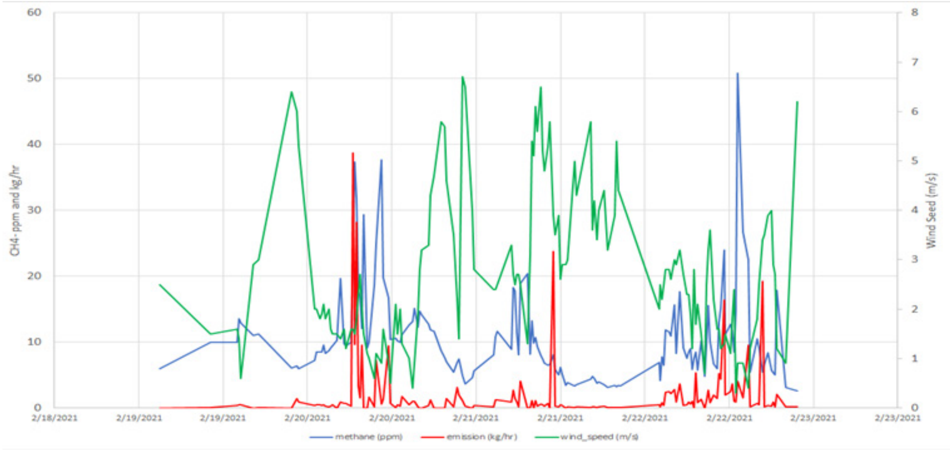

Figure 7 shows the emission rate data as a wind rose indicating the number of detections of emissions by wind direction. It is clear from Figure 7 that the emissions were more consistently measured when the winds came from the west and the west southwest, further highlighting the reliance of continuous monitoring systems on the wind to carry the emissions to a location that can be measured by the sensor. The wind rose also demonstrates the difficulty of locating emission sources without some form of visualization. Instead, advanced analytics must be used to attempt to determine the origin of the emission.

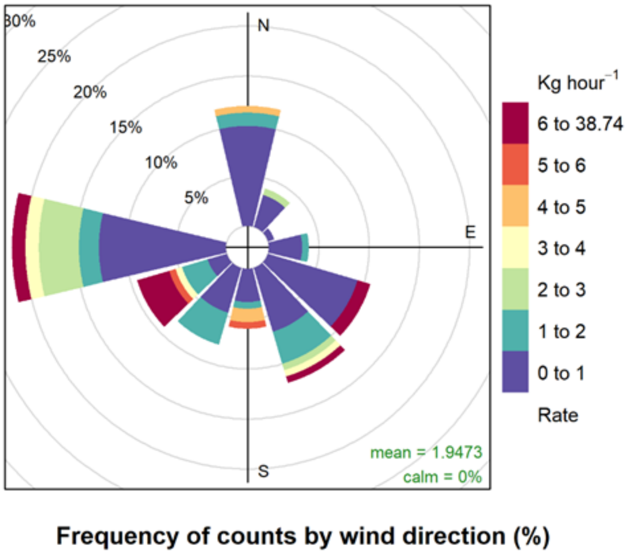

Figure 7. A wind rose showing the CM data by wind direction

The GTI dataset contains some other CM data reporting an emission rate (flux) measurement at two locations spanning over 6,000 hours of observation. The data provided to GTI does not contain wind speed and direction, only emission rate, but this does not mean the information would not be collected by a vendor. Figure 8 shows a histogram of the emission rates for 2,200 hours at one site in the Permian. This data needs to be viewed as a time-series, as shown in Figure 9, to fully interpret the histogram and what may be occurring at the site.

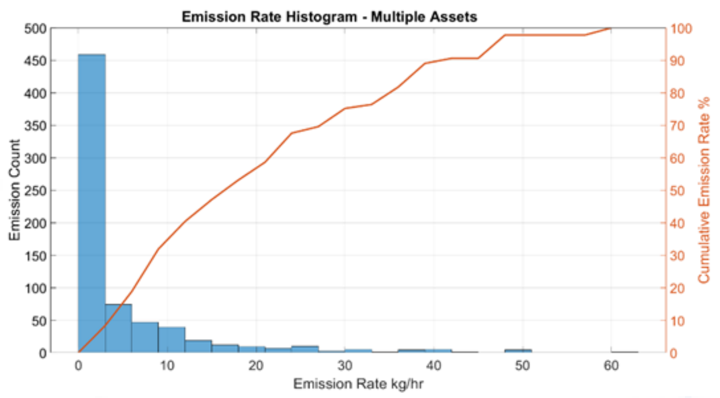

Figure 8. Histogram of showing 2200 hours of CM data at a single site in the Permian Basin.

The emission rate data is highly variable and several possible conclusions can be drawn. One of those conclusions could be that the site may be experiencing a large intermittent emission. The transient nature of the emissions indicates that there is a possibility that the emission may not be found if the site is visited during one of the “low emission” times. Therefore, this type of data would require a follow-up investigation either through examination of SCADA data or by ground crews at the appropriate times to locate the emission source.

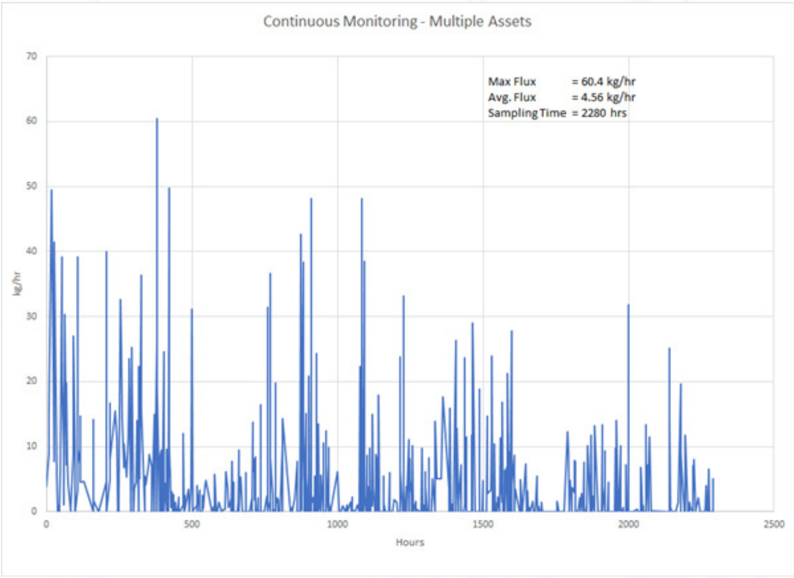

Figure 9. Time series of 2,200 hours of data from a CM sensor in Permian Basin.

Although highly variable at some sites, the following use case of the CM data provides an excellent example of the potential usefulness of the technology. This occurred when an anomalous CH_4 release was detected as shown in Figure 10, which triggered an alert that led to mitigation. A pressure relief valve at a gas well site was found to be venting due to fluctuations in line pressure. A regulator was placed upstream that limited fluctuations and venting. During the release, the operator lost ~$24,000 (assuming $4/MCF) and emitted close to 6,100 kgs of methane. If the unintended release had been allowed to continue during the sampling time, the operator would have lost close to $1.8 million.

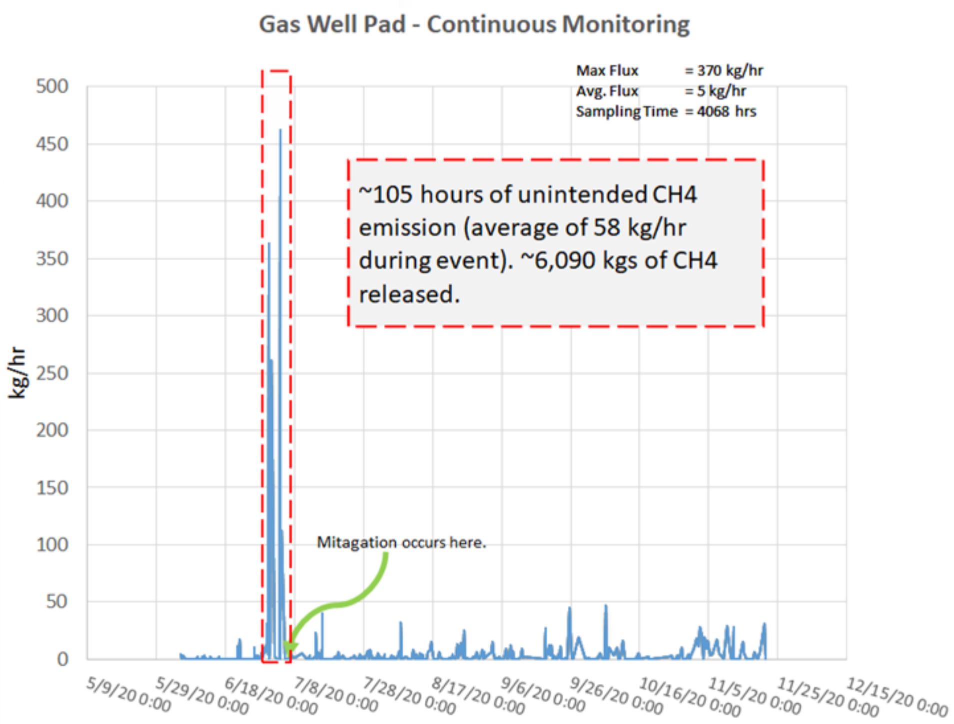

Figure 10. Example of an emission detection leading mitigation with a CM system.

Emissions and Cost Scenario Analysis—Case Studies

Methodology: LDAR Program Emissions and Cost Modeling

The case studies presented above provide compelling examples of how emerging methane measurement methodologies can be used to detect a broad range of methane sources. However, it is difficult to infer emissions mitigation from detection-only data because baselines are difficult to establish. Furthermore, cost data is difficult to come by for emerging technologies and may not be representative at this time because most technologies are at an early stage in the innovation cycle. Together, estimates of mitigation and cost can provide insight into the value of these new technologies in terms of their cost of mitigation. Most commonly, cost of mitigation is expressed in dollars per metric ton of carbon dioxide equivalent ($/tCO$_2$e). Cost of mitigation expressed in these terms is a universal language that can be used to compare the returns on investment of diverse mitigation strategies.

The case studies from the previous section were used to inform engineering estimates on costs and detection limits in the simulations that can provide insight to likely mitigation scenarios. Ranges of cost estimates were established using expert knowledge and data provided from both operators and solution providers. These data were then combined in the Leak Detection and Repair Simulator (LDAR-Sim) to estimate emissions reductions from a baseline scenario in the absence of LDAR and generate cost of mitigation distributions (Fox et al., 2021a, Fox et al., 2021b). LDAR-Sim is an open-source, agent-based numerical simulation tool that is used to estimate the emissions reduction performance and cost-effectiveness of various LDAR technologies. LDAR-Sim is peer-reviewed and is recognized by regulators, industry, and innovators around the world as a credible means of evaluating existing and emerging methane measurement technologies.

Results are presented in the following sections. In general, different technologies achieve a broad range of estimated mitigation performance depending on a combination of system sensitivity and frequency of measurement. Methodologies with the lowest sensitivity (highest MDLs) tend to have a low cost of mitigation but may miss smaller leaks by only focusing on large, high-value sources. More sensitive methodologies tend to be more expensive because instrumentation must be more precise and because work practices require more meticulous attention to smaller leaks. These systems mitigate more emissions but tend to do so at a higher cost, on average. In general, the cost of mitigation observed for most emerging methodologies for the case studies presented in this report is strongly competitive in comparison to other opportunities for reducing emissions.

LDAR-Sim and technology modules

Information in the collected dataset, assembled costs, and additional general assumptions were used to conduct detailed cost modeling for a variety of emissions and detection scenarios. The modeling conducted with LDAR-Sim was used to gain a deeper understanding of the costs to implement the methodologies and determine the cost of mitigating methane in terms of U.S. dollars per metric ton of mitigated carbon dioxide equivalent of fugitive methane ($/tCO$_2$e).

We use known emissions distributions (Zavala-Araiza et al., 2015; Bell et al., 2017) to create a 'virtual world' case studies for testing methodologies on production sites (i.e., typical emitting) and compressor stations (i.e., high emitting) within the Barnett shale gas play and on production sites in the Fayetteville shale gas play (i.e., low emitting) to present a range of scenarios/ case studies. These provide a plausible range of emissions distributions for oil and gas facilities throughout the U.S. and would encompass the range of distributions in the areas of the Permian covered in the GTI data set. The emissions from leaks identified by Bell et al. 2017 at production sites in the Fayetteville region are generally smaller and we assume, illustrate a profile of lower-emitting facilities. The distributions identified by Zavala-Araiza et al. 2015 for production sites and compressor stations are orders of magnitude larger and are generally heavier tailed due to the inclusion of more super emitters and generally fit leak profiles observed in the Permian (e.g., Cusworth, et al., 2021). We assume the production site distribution represents a profile of typical emitting facilities and that the compressor station distribution represents a profile of high-emitting facilities.

Technologies outlined by GTI were used to create LDAR-Sim modules. Various simulations were carried out with the three emissions profiles described above (Barnett production sites, Barnett compressor stations, and Fayetteville production sites). Table 2 and Table 3 show the LDAR-Sim parameters used in simulations. It is important to note the difference in naming conventions between the general method and the full program that includes any follow up. For example, OGI refers to the OGI work practice while P_OGI refers to an entire program based only OGI. CM_WP_1 refers to the CM work practice with higher cost and lower MDL while P_CM_1 refers to the full program that uses the CM_WP_1 work practice along with OGI follow-up. Default LDAR-Sim parameters outlined in the LDAR-Sim V2.0 User Manual were used except for emission distributions (see Table 3), number of simulations (40), detection method MDL, costs, and survey times. *Costs, MDLs, and survey times were obtained through the dataset and by expert knowledge and represent hypothetical case studies specific to this report and should not be interpreted as defaults, typical values, or industry averages.*

LDAR technology comparison across different leak rate distributions with fixed survey frequency

We modeled 7 different detection programs against a baseline scenario where no formal LDAR is employed. Following EPA's proposed OOOOb and OOOOc, all screening technologies, except for CM sensors, receive 6 annual screenings with OGI follow-up along with an annual OGI survey at all sites. Continuous monitoring sensors survey include OGI follow-up and a single annual survey at all sites. The OGI method receives 4 annual OGI surveys. Each varies in cost, MDL, and survey time per site. All, except the OGI program, are modeled as screening surveys that require close-range follow-up inspections to tag leaks. Follow-up surveys are modeled using the OGI method, which uses the same parameters as those in Table 3. Detailed flow charts of the process are depicted in Figure 25 and Figure 26 in the Appendix. We apply the programs at 500 sites and run 40 times for each program to stratify the results, removing variance from the models' random variables, while providing more data points for determining cost of mitigation.

The outputs of LDAR-Sim provide estimates of 1) average mitigated emissions, 2) breakdown of mitigated emission by detection method, 3) statistics of daily emissions, 4) cost and cost breakdown, and 5) cost mitigation of each program. Average mitigated emissions refer to the difference in total emissions of a leak in a program with no formal LDAR and in a program with formal LDAR, i.e., $E_{mit} = \theta_{leak} \times (t_{None} - t_{LDAR})$. Where E_{mit} is the mitigated emissions, θ_{leak} is the leak rate, and t_{None} and t_{LDAR} are the duration where the leak is active for a program with and without formal LDAR, respectively. Aside from uncertainties in model parameter selection, results are likely sensitive to emissions intermittency which has not been included in these modeled case studies.

Mobile screening and survey LDAR comparison at Barnett processing sites with varying survey frequencies

We then ran simulations using LDAR-Sim to compare emissions reduction performance at different survey frequencies (i.e., number of inspections per year) for mobile methods (i.e., continuous measurement is excluded from this analysis). Using the Barnett production leak rate distribution and the parameters shown in Table 2 and Table 3 we run simulations with 1, 2, 4, 6, and 12 surveys per year (frequency) for all mobile screening methods. The results are used to show the effect of changing survey frequency on emissions and are presented towards the end of the results section.

Table 2. Virtual world parameter list for simulations in the Barnett and Fayetteville plays

Virtual World

Parameter	Value	Source
Region	Barnett (B), Fayetteville (F)	
Infrastructure source	Production Sites (B+F), Compressor Stations (B)	--
Sites sampled	500	--
Empirical leak distribution source	Various	--
Leak sampling	Lognormal (kg/hr)	--
F – Production: Emissions lognormal params [mu, sigma]	[-2.89, 1.57]	Bell et al., 2017
B – Production: Emissions lognormal params [mu, sigma]	[-1.79, 2.17]	Zavala-Araiza et al., 2015
B – Mid Stream: Emissions lognormal params [mu, sigma]	[3.05, 1.49]	Zavala-Araiza et al., 2015
Repair delay (days)	15	Expert Knowledge
LPR (leaks per day per site)	0.0065	Fox et al., 2021a
Days to natural repair	365	Expert Knowledge
Number of years	5	--
Number of simulations per program	40	--

Table 3. Technology module LDAR-Sim modeling parameters.

Program Name: P_OGI	
work practice	OGI
MDL (k)	0.05 kg/hr
cost per survey ($)	500
upfront cost ($)	0
quantification error (%)	0
survey time (min/site)	76
frequency (surveys/year)	4*
max workday (hours)	8
travel time (min/site)	30
number of OGI crews	3
extra OGI surveys per year	0
average sites per day	4.25

Program Name: P_Drone	
work practice	Drone
MDL (k)	5.0 (kg/hr)
cost per survey ($)	650
upfront cost ($)	0
quantification error (%)	0
survey time (min/site)	76
frequency (surveys/year)	6*
max workday (hours)	8
travel time (min/site)	30
number of OGI FU crews	1
extra OGI surveys per year	1
average sites per day	4.25

** Survey frequencies 1, 2, 4, 6, and 12 are used in the section: Mobile screening and survey LDAR comparison at Barnett processing sites with varying survey frequencies*

Program Name: P_Aerial_3	
work practice	Aerial_3
MDL (k)	1.0 (kg/hr)
cost per survey ($)	300
upfront cost ($)	0
quantification error (%)	0
survey time (min/site)	2
frequency (surveys/year)	6*
max workday (hours)	8
travel time (min/site)	1
number of OGI FU crews	1
extra OGI surveys per year	1
average sites per day	160

Program Name: P_Aerial_2	
work practice	Aerial_2
MDL (k)	5.0 (kg/hr)
cost per survey ($)	200
upfront cost ($)	0
quantification error (%)	0
survey time (min/site)	1
frequency (surveys/year)	6*
max workday (hours)	8
travel time (min/site)	1
number of OGI FU crews	1
extra OGI surveys per year	1
average sites per day	240

Program Name: P_Aerial_1	
work practice	Aerial_1
MDL (k)	20.0 (kg/hr)
cost per survey ($)	100
upfront cost ($)	0
quantification error (%)	0
survey time (min/site)	0
frequency (surveys/year)	6*
max workday (hours)	8
travel time (min/site)	1
number of OGI FU crews	1
extra OGI surveys per year	1
average sites per day	480

Program Name: P_CM_1	
work practice	CM_WP_1
MDL (k)	10.0 (kg/hr)
cost per survey ($)	10
upfront cost ($)	1000
quantification error (%)	0
survey time (min/site)	NA
frequency (surveys/year)	365
max workday (hours)	NA
travel time (min/site)	NA
number of OGI FU crews	1
temporal coverage	0.25
extra OGI surveys per year	1

Program Name: P_CM_2	
work practice	CM_WP_2
MDL (k)	0.05 (kg/hr)
cost per survey ($)	18
upfront cost ($)	4000
quantification error (%)	0
survey time (min/site)	NA
frequency (surveys/year)	365
max workday (hours)	NA
travel time (min/site)	NA
number of OGI FU crews	1
temporal coverage	1
extra OGI surveys per year	1

Note: Extra OGI and OGI FU have the same parameters as the OGI method aside from survey frequency.

* *Survey frequencies 1, 2, 4, 6, and 12 are used in the section: Mobile screening and survey LDAR comparison at Barnett processing sites with varying survey frequencies*

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Results: LDAR Program Emissions and Cost Modeling

LDAR technology comparison across different leak rate distributions with fixed survey frequency

Barnett production sites (typical emitting)

Simulated mitigated emissions from programs defined in Table 3 (with fixed survey frequencies), as shown in Figure 11, are the highest for the continuous monitor method with high frequency operations and lowest for the aircraft with the highest MDL for the Barnett production site (typical emitting) scenario. This is a result of both a higher MDL and survey frequency of monitoring where CM can have MDLs like those of an OGI camera and perform screening daily. All technologies show a significant improvement in reductions comparable with that of using 4x annual OGI (P_OGI, Figure 13), although only P_CM_2 and P_Aerial_3 (lowest MDL) show an improvement over P_OGI (Figure 11). Figure 12 shows that the inclusion of a single annual OGI added into a screening program can effectively reduce emissions for some of the higher MDL programs, for example nearly 40% of the mitigated emission from P_Aerial_1 was attributed to the single OGI screening. In contrast, less than 1% of mitigated emission from P_CM_2 was attributed to the annual OGI. For this case study of Barnett production sites, the additional 1x OGI into all but P_CM_2 seems necessary in providing an equivalent emissions reduction when compared to the 4x annual OGI program.

Program costs per site, as shown in Figure 14, are the highest for P_CM_2 while P_Aerial_1 is the least costly. The higher cost for P_CM_2 is both due to daily operating costs, and the requirement of frequent OGI follow-ups. Cost mitigation ratios for production sites in the Barnett, as shown in Figure 15, are the highest for P_CM_2, while P_ Aerial_3 has the lowest. Cost of mitigation is largely driven by the program cost, as most programs have comparable abilities to mitigate emissions.

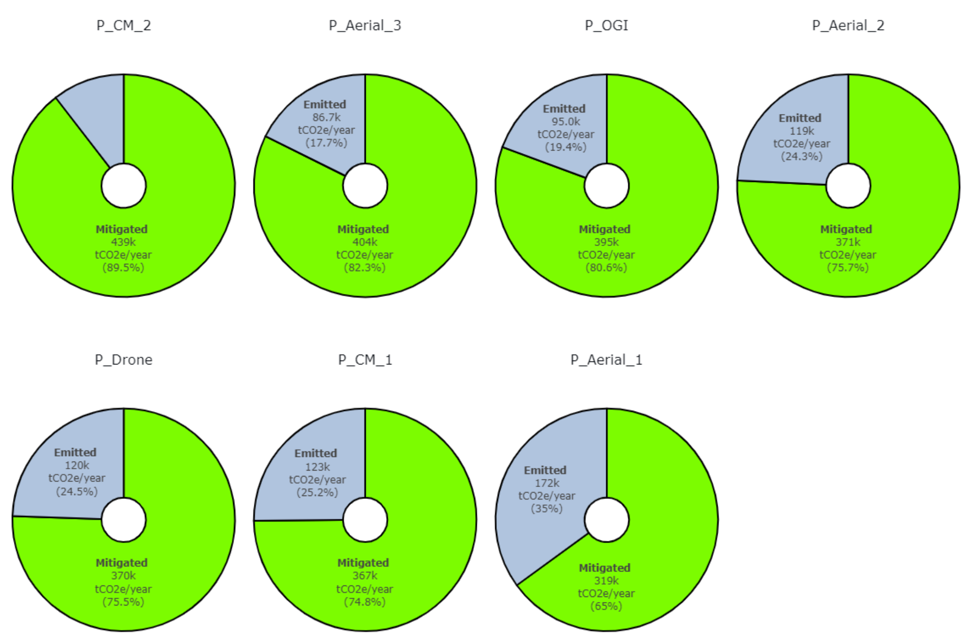


Figure 11: Breakdown of emissions (CH_4) by program (emitted = slate, mitigated = green) at Barnett production sites over 5 years with 4x annual OGI surveys / 6x screenings with OGI FU and 1x OGI annual survey.

Figure 12: Breakdown of mitigated emissions by initial detecting program at Barnett production sites over 5 years.

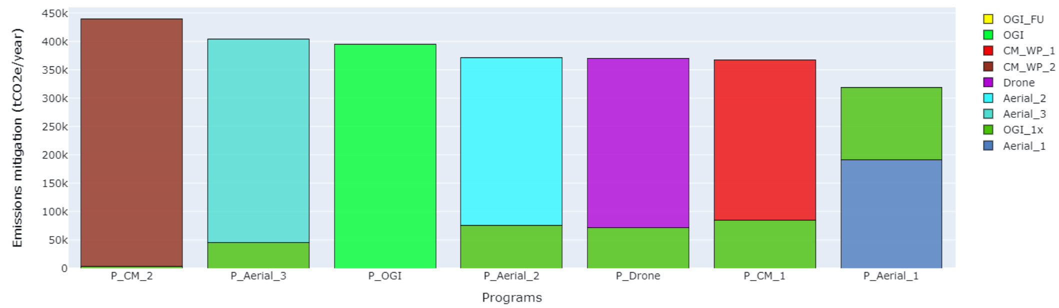


Figure 13: Distribution plot of simulated emissions (CH_4) where each data point is system-wide site average emissions for each simulated day and for each program at Barnett production sites over 5 years.

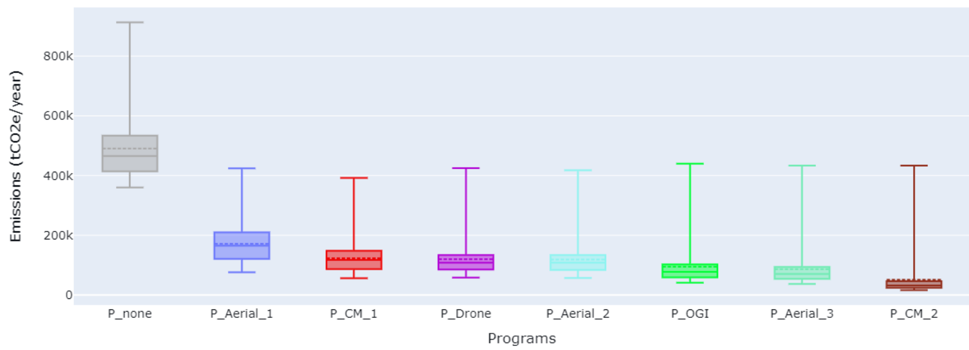


Figure 14: Annual cost per site at Barnett production sites. Includes upfront costs of technologies.

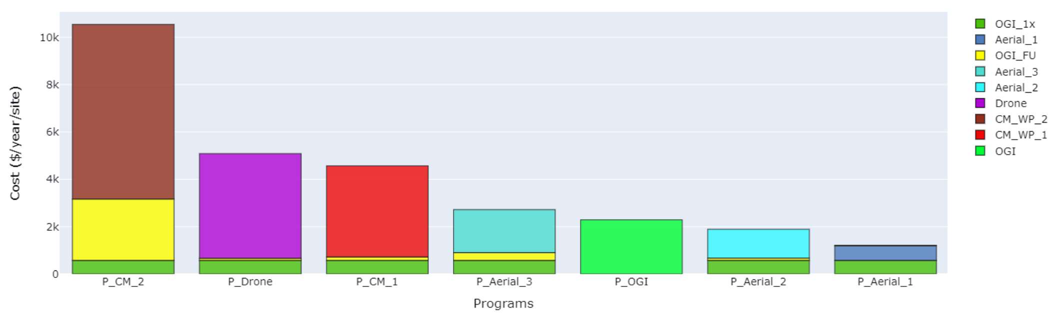
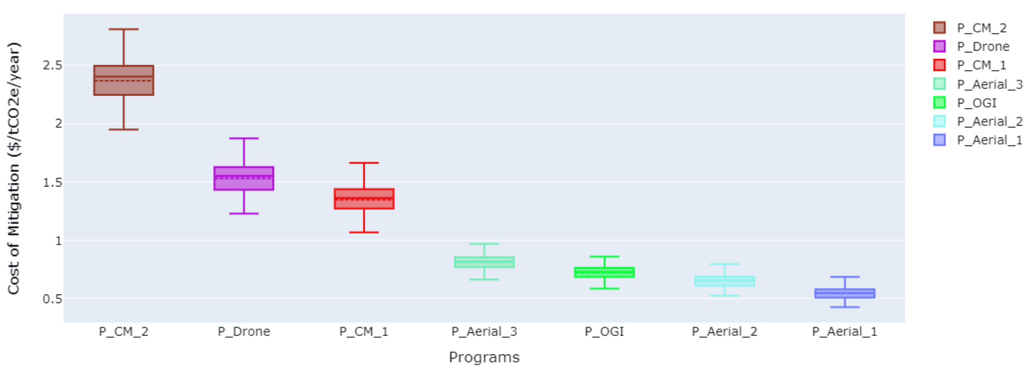


Figure 15: Cost-mitigation ($/$CO_2$e/year) distribution plot where each data point is system-wide ratio of total program cost to total program mitigated emissions at Barnett production sites. Forty independent 5-year simulations were run for each program.



Barnett compressor stations (high emitting)

Simulated mitigated emissions as shown in Figure 16, are the highest for the P_CM_2 and lowest for the 4x annual OGI program (P_OGI) for the Barnett compressor station (high emitting) scenario. All technologies show a significant improvement in reductions and show potential equivalency with P_OGI (Figure 17). Figure 18 shows that the inclusion of a single annual OGI added into a screening program can effectively reduce emissions for some of the higher MDL programs, for example nearly 9% of the mitigated emission from P_Aerial_1 was attributed to the single OGI screening, which is enough improve emissions reduction to equivalence with P_OGI. In contrast, less than 2% of mitigated emission from P_CM_2 and P_CM_1 are attributed to the annual OGI work practice. For this case study of Barnett compressor stations, the additional 1xOGI into all but the programs with continuous monitoring technologies are necessary in providing an equivalent emissions reduction when compared to the 4x annual OGI program. However, the reliance of the 1xOGI to achieve equivalence is less so for higher emitting sites then for lower emitting sites.

Program costs and costs of mitigations for high emitting compressor stations, as shown in Figure 19, were the highest when CM technologies were employed and lowest for P_Aerial_1. Similar to Barnett production sites, the higher cost of mitigation with CM technologies is due to both higher operating costs and more frequent OGI follow-up. Interestingly, cost mitigation is two orders of magnitude smaller for all methods with Barnett compressor stations compared to Barnett production stations. This is a result of the total emissions increasing several orders of magnitude, while the increase of cost was smaller, and was only a result of additional follow-up OGI surveys for screening methods.

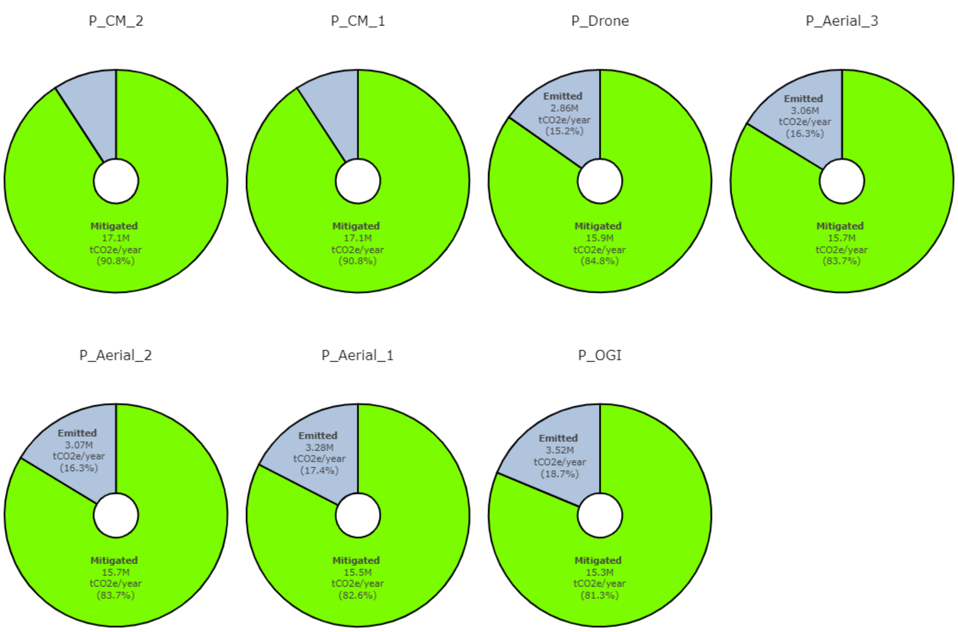


Figure 16: Breakdown of emissions (CH_4) by program (emitted = slate, mitigated = green) at Barnett compressor stations over 5 years with 4x annual OGI surveys / 6x screenings with OGI FU and 1x OGI annual survey.

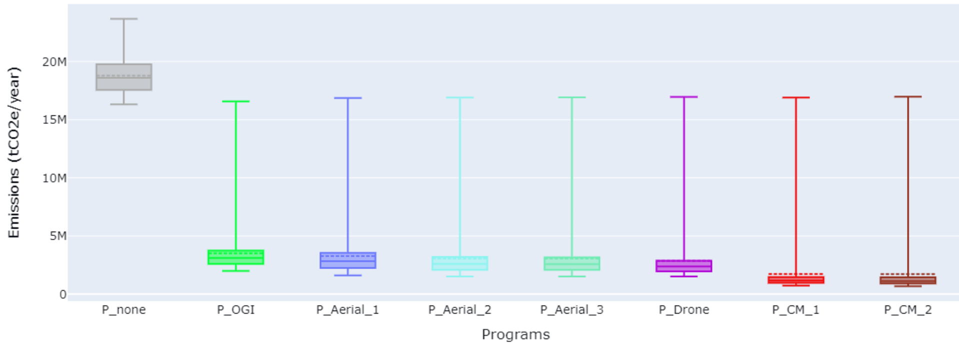


Figure 17: Distribution plot of simulated emissions (CH_4) where each data point is system-wide site average emissions for each simulated day and each program at Barnett Compressor Stations over five years.

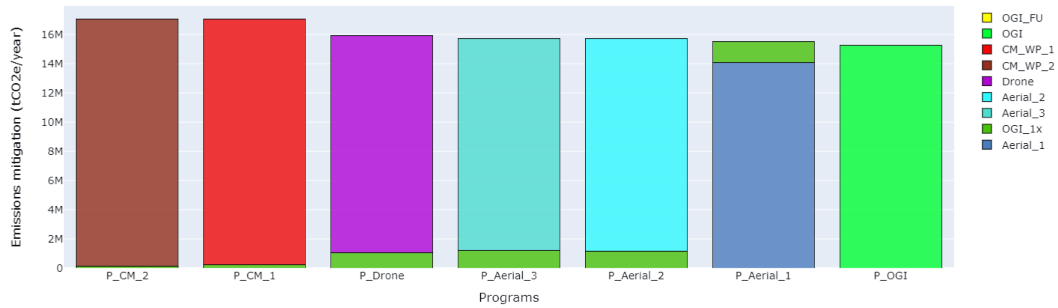


Figure 18: Breakdown of mitigated emissions by initial detecting program at Barnett compressor stations.

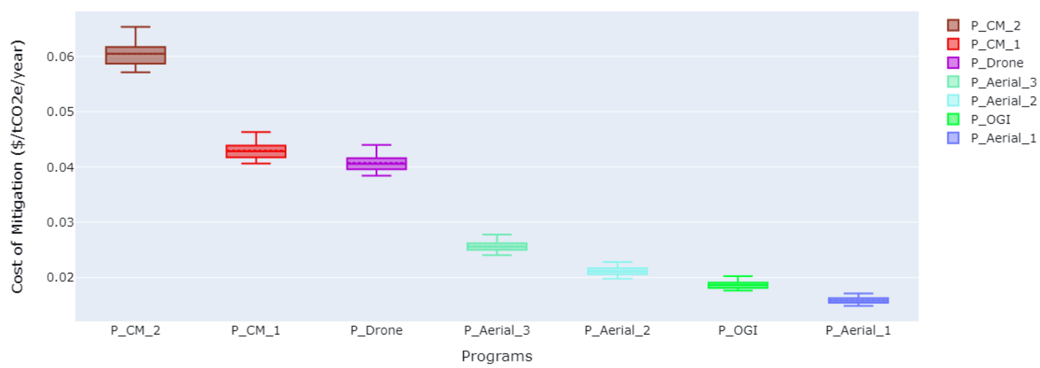


Figure 19: Cost-mitigation ($\$/tCO_2e/year$) distribution plot where each data point is system-wide ratio of total program cost to total program mitigated emissions at Barnett compressor stations. Forty independent 5-year simulations were run for each program.

Fayetteville production sites (low emitting)

As shown in Figure 20, simulated mitigated emissions are the highest for P_CM_2 and lowest for the 4x annual P_Aerial_1 for the Fayetteville production site (low emitting) scenario. All technologies show a significant improvement in reductions (Figure 17). Figure 22 shows that the inclusion of a single annual OGI added into a screening program can effectively reduce emissions for all programs, for example nearly 98% of the mitigated emission from P_Aerial_1 was attributed to the single OGI screening. In contrast, less than 1% of mitigated emission from P_CM_2 is attributed to the inclusion of an annual OGI.

Like production stations and compressor stations in the Barnett, costs for production stations in the Fayetteville play, are the highest when CM technologies are employed, P_Aerial_1 is the least costly. Although unlike compressor stations and production sites in the Barnett, costs from Fayetteville have minimal contributions from follow-up surveys due to fewer detections from screening technologies. The exception to this is P_CM_2, where the sensor is sensitive enough to detect the smaller leaks common in the Fayetteville distribution. Cost mitigation ratios for production sites in the Fayetteville play, as shown in Figure 23, are again the highest for P_CM_2. Although P_OGI is the second most costly program to use, here it is modeled to be the most cost-effective approach at reducing emissions.

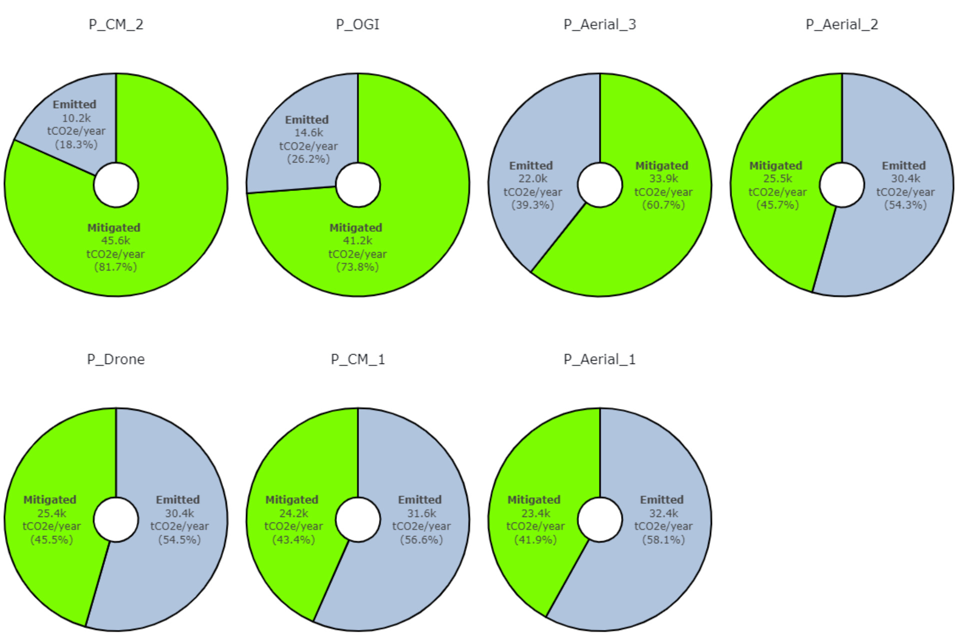


Figure 20: Breakdown of emissions (CH_4) by program (emitted = slate, mitigated = green) at Fayetteville production sites over 5 years with 4x annual OGI surveys / 6x screenings with OGI FU and 1x OGI annual survey.

Figure 21: Distribution plot of simulated emissions (CH_4) where each data point is system-wide site average emissions for each simulated day and for each program at Fayetteville production sites over 5 years.

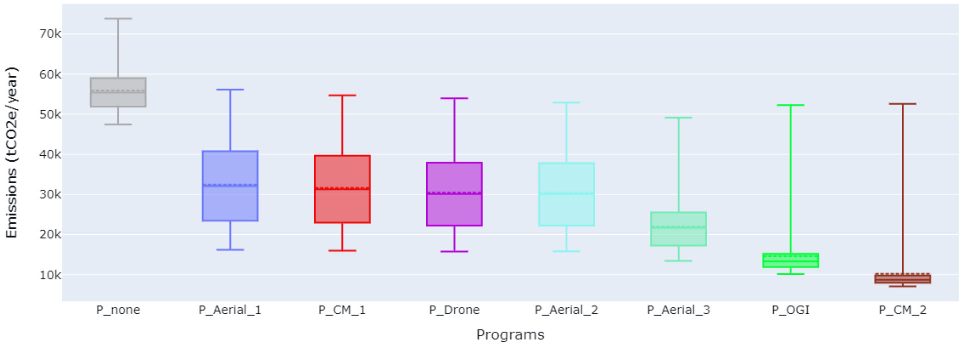


Figure 22: Breakdown of mitigated emissions by initial detecting program at Fayetteville production sites at Fayetteville production sites over 5 years.

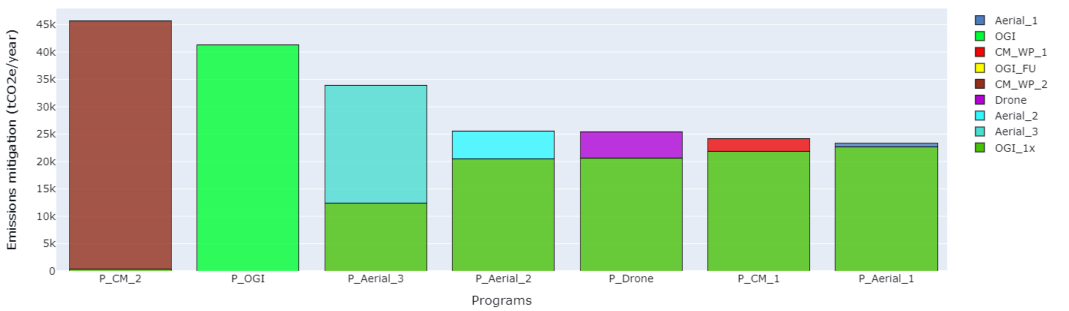
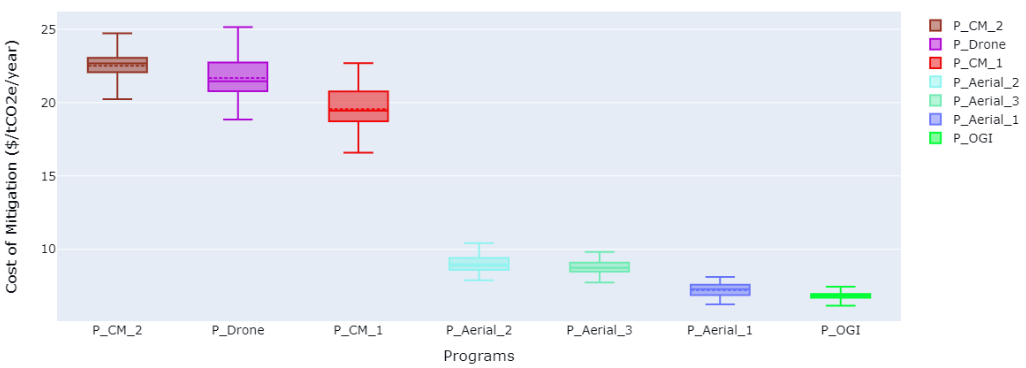


Figure 23: Cost-mitigation ($/tCO$_2$e/year) distribution plot where each data point is system-wide ratio of total program cost to total program mitigated emissions at Fayetteville production sites. Forty independent 5-year simulations were run for each program.



Results: Mobile screening and survey LDAR comparison at Barnett processing sites with varying survey frequencies.

For all mobile (aerial, drone, OGI) work practices/methods, as the number of annual surveys increases, the percentage of modeled mitigated emissions also increases (Figure 24). However, we found that there is a diminishing return, where for example the percentage of emissions mitigated in the Aerial_1 program was roughly the same whether aerial surveys were performed 6 times a year or 12 times a year. Like the results from the previous section, P_ OGI had a higher mitigation percentage than the screening methods. Notably, it took 4, 2, 1, and 2 surveys per year respectively (with OGI follow-up) using the Aerial_1, Aerial_2, Aerial_3 and Drone systems to achieve equivalent or better mitigated emissions as annual OGI. The diminishing return of surveys and screenings in modeling is a result of a leak production rate (LPR) value, where an LPR of 0.0065 leaks/day/site or 2.34 leaks/year/site will result in few leaks, and smaller emissions found on each subsequent survey.

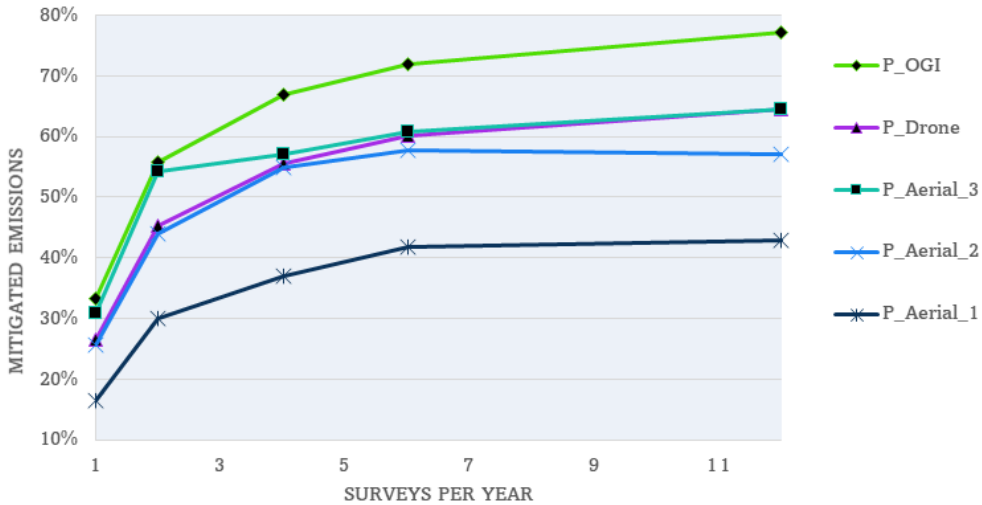
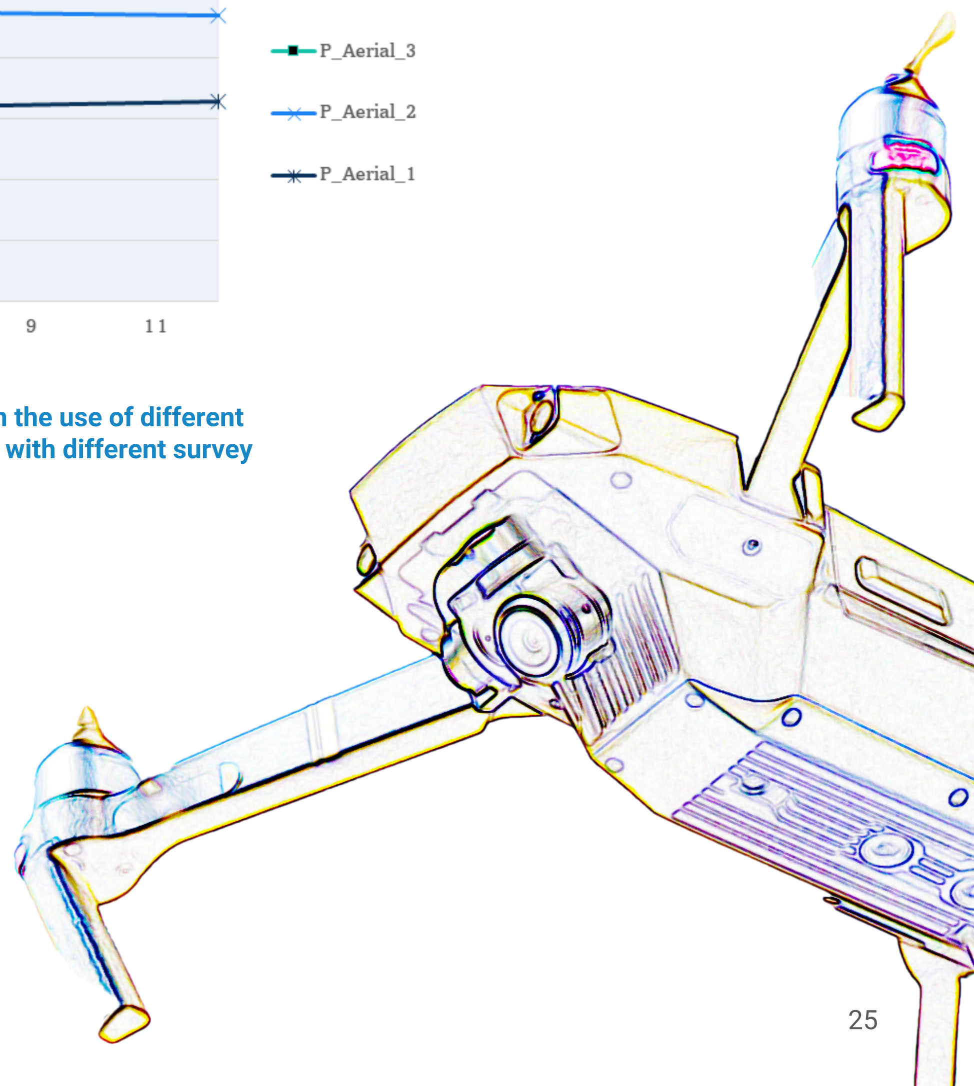


Figure 24: Estimated emissions mitigation from the use of different technologies on production sites in the Barnett with different survey frequencies.



Concluding Remarks

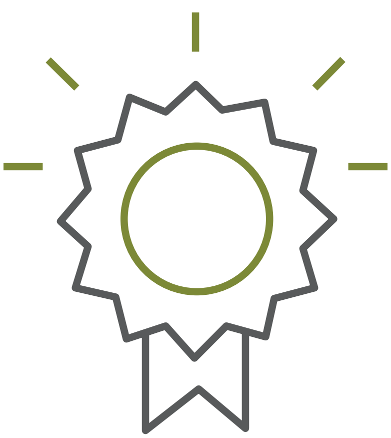
While hundreds of data files were shared with GTI containing hundreds of thousands of data points, it is important to note that each methodology:

- Operates according to very different sensing principles
- Is deployed using different work practices
- Employs different analytics to estimate source location and emission rates,
- Reports different information to the end user.
- Represents only a case study in this report for how the methodology may be implemented

There are no data reporting standards for these methodologies, so for the purposes of the study, GTI focused on the use cases and other ways that the data could be used to explore the performance of advanced methane detection methods. *It is important to note that the LDAR programs detailed and simulated in this report represent hypothetical case studies and are not immutable representations of any given technology or technology class.* General consensus exists that various solutions perform better or worse under different conditions and that no solution is a ‘silver bullet’.

Ultimately, the programs show a varied range of emissions reduction where a continuous monitoring sensor with a handheld follow-up survey is the most effective, while a higher minimum detection limit (MDL) and higher number of sites per day aircraft conducted on an annual survey frequency had the lowest mitigated emissions and lowest cost of mitigation.

As demonstrated by Figure 24, while emissions continue to decrease with increased survey frequency, there are diminishing returns in emissions reduction with increasing survey frequency for aerial technologies with different MDLs (High MDL, 20kg/hr = Aerial_1, Medium MDL, 10 kg/hr = Aerial_2, Low MDL, 5kg/hr = Aerial_3).



CM sensors demonstrated the highest reduction in emissions, but also cost substantially more on a cost of mitigating methane in U.S. dollars per metric ton of mitigated carbon dioxide equivalent of fugitive methane ($/t$CO_2$e).

Importantly, every methane detection technology resulted in a reduction of emissions with varying effectiveness and varying mitigation cost. CM sensors were the most effective at reducing emissions, but at the highest cost to deploy and mitigate. On the other hand, high MDL aircraft-based technologies (Aerial_1) had the lowest cost per ton to mitigate emissions, but was capable of mitigating the smallest percentage of emissions.

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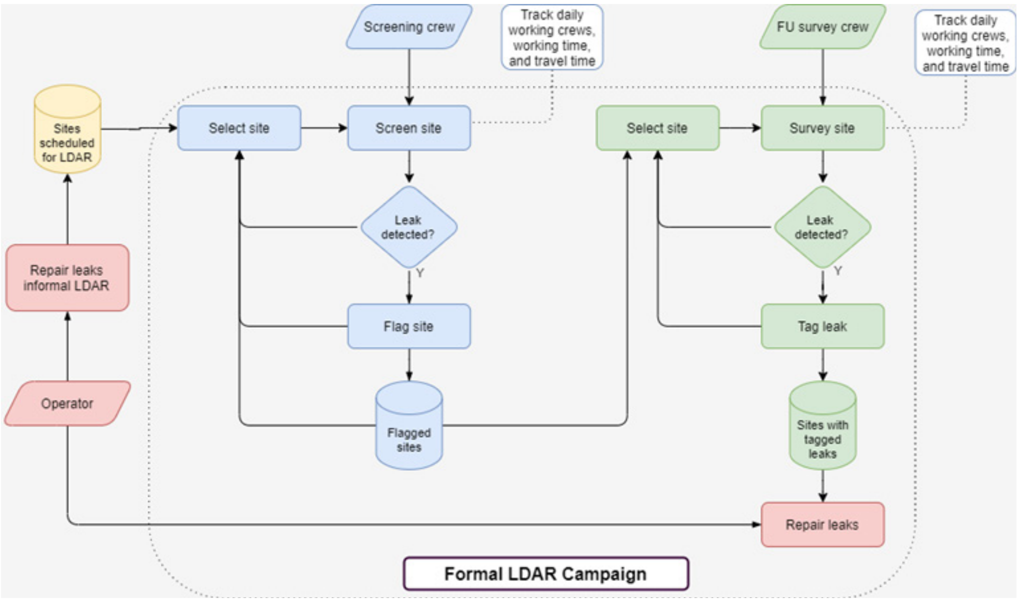
Appendix

Figure 25: LDAR-Campaign with Screening Technology and Survey follow-up



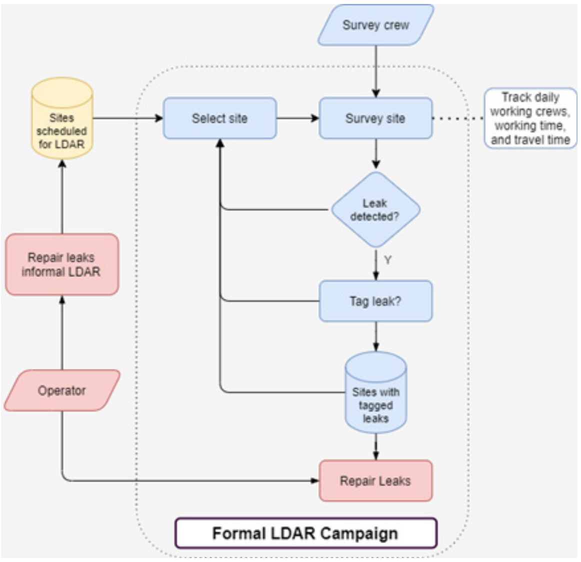


Figure 26: LDAR-Campaign with Survey Technology

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