Tiered Leak Detection and Repair Programs at Oil and Gas Production Facilities

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Abstract

Methane emission rates originating from oil and gas production facilities are highly skewed and span 6-8 orders of magnitude. Traditional leak detection and repair programs have relied on surveys with handheld detectors at intervals of 2 to 4 times a year to find and fix emissions, however this approach leads to leaks being active for the same interval independently of their magnitude. In addition, manual surveys are labor intensive. Novel methane detection technologies offer opportunities to further reduce emissions by quickly detecting the high-emitters, which account for a disproportionate fraction of total emissions. In this work, combinations of methane detection technologies were simulated in a tiered approach for facilities representative of the Permian Basin, a region with skewed emission rates and large numbers of high-emitters, which include sensors on satellites, aircraft, continuous monitors and Optical Gas Imaging (OGI) cameras, with variations on survey frequency, detection thresholds and repair times. Results show that in oil and gas production regions with skewed emission rates and large numbers of high-emitters, strategies that increase the frequency of surveys targeting high-emitters while decreasing the frequency of OGI inspections, which find the smaller emissions, achieve higher reductions than quarterly OGI and, in some cases, reduce emissions further than monthly OGI.

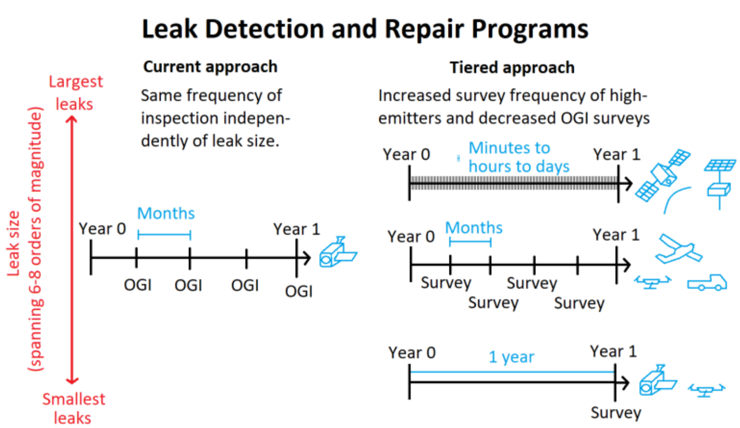
Keywords

Leak detection and repair; methane; greenhouse gas emissions; oil and gas.

Synopsis

Tiered leak detection and repair programs using novel methane detection technologies that quickly find and fix high-emitting sources achieve higher emission reductions than manual programs at fixed intervals.

TOC art



Introduction

Methane is a potent greenhouse gas which exerts the second largest climate forcing after carbon dioxide.[1] Rapid reductions on methane emissions are needed to limit global warming to 1.5°C. As such, in 2021 nations around the globe signed the Global Methane Pledge, committing to reduce their collective methane emissions 30% from 2020 levels by 2030.[2] Atmospheric methane has multiple natural and anthropogenic origins, with activities from coal mining and oil and natural gas systems accounting for ~18% of global emissions for the year 2017.[3] Emissions from the oil and natural gas systems are seen as the sector that can account for the majority of emission reductions by 2030 and multiple companies have set targets for emission reduction.[4]

Multiple studies performed over the last decade have improved the knowledge of emissions occurring along oil and gas supply chains and have shown that emission distributions are highly skewed,[5,6] with a few number of sources accounting for a large fraction of emissions. The variation of emission rates can be significant, with emission rates spanning six to eight orders of magnitude (Figure 1a).[7,8] Emission rates reported from these studies are snapshots, however absolute emissions are given by the time a leak is active and by its emission rate. One strategy to reduce emissions from oil and gas activities is through mitigation of un-intended emissions in Leak Detection and Repair Programs (LDAR), which shorten the time that leaks are active.

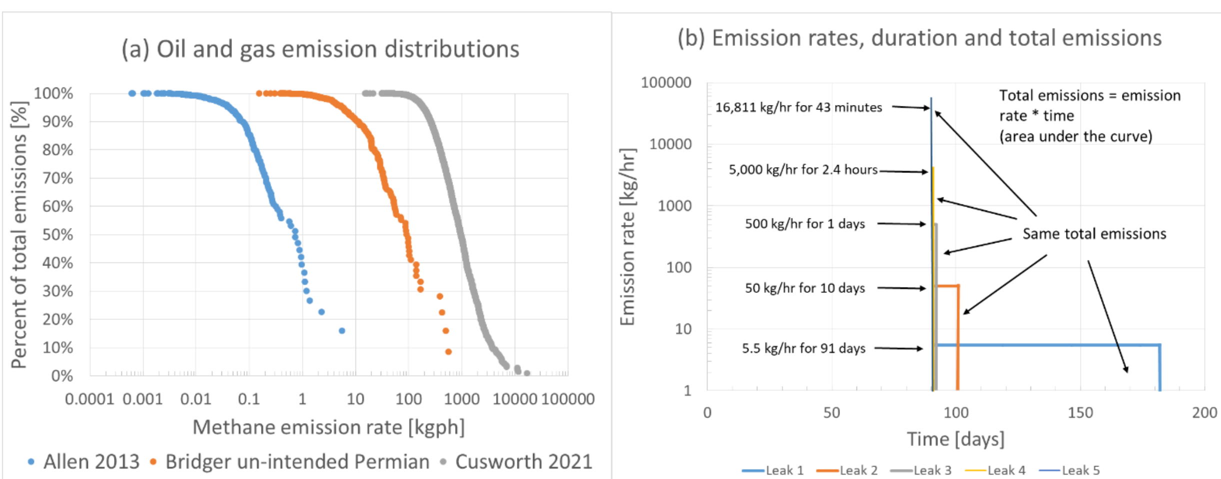


Figure 1. (a) Emission distributions from oil and gas infrastructure, and (b) same total emissions for various emission rates and durations.

The highest methane emission rate reported by Allen et al.,[7] in a study that sampled production sites in multiple basins with Optical Gas Imaging (OGI) cameras, was 5.5 kg/hr. If this leak was active for 91 days (half of the time between two times a year LDAR inspections) it would release the same amount of methane that the highest emission rate from a study surveying the Permian basin using aircraft based measurements[8] would, if it was active for less than an hour (Figure 1b). Thus, high emission rates active for a relatively short amount of time can have a significant impact on total emissions, so they should be detected and fixed quickly.

Traditionally LDAR programs have relied on OGI or method 21 with inspections two or four times a year, which, until recently were the only options allowed by federal regulations.[9] Under this approach the time between surveys has been independent of the size of leaks, leading to leaks with high emission rates to potentially be active for large amounts of time before they are found. However, in recent years, there have been rapid advancements in technologies to detect methane with sensor platforms including aircraft, satellites, drones, fixed monitors or cameras on pads and trucks, offering opportunities for LDAR programs with greater emission reductions and that are less labor intensive than conventional approaches.[10]

In order to compare the reduction in emissions between LDAR programs, computational models such as FEAST[11]or LDAR-Sim[12] have been developed. With these models it has been demonstrated that novel technologies can achieve at least the same reduction as two or four times a year OGI, and that OGI inspections are still needed in follow-ups from the novel technologies to find the smallest leaks.[13] However studies that employ these models have not evaluated combinations of multiple technologies nor continuous monitors. In addition, these studies have simulated facilities with the same equipment and components, while the types of equipment can vary depending on their vintage and throughput.

Multiple studies have shown that emissions from oil and gas activities are larger than reported emissions, and the discrepancy is attributed to large un-intended emissions.[14,6] There is a need to achieve emission reductions in a way that is effective and safe, as frequent inspections using manual OGI cameras require extensive driving between facilities. This work will explore LDAR programs that rely on combinations of methane detection technologies, focusing on quickly detecting and fixing the highest emitters, while decreasing the number of OGI inspections. The facilities simulated are heterogeneous and representative of the Permian Basin, which is an oil and gas production basin with large numbers of high-emitters.[8,15,16]

Methodology

This work uses a model based on the leak module of the Methane Emission Estimation Tool (MEET),[17,18] with the inclusion of LDAR programs. The resulting model is similar in operation to other open source LDAR models,[11,12] but has some differences that are detailed in the following sections. The simulation is stochastic and each LDAR scenario was ran in a Monte Carlo approach 50 times to get a range of reductions. The temporal resolution of the simulation was one day and was ran for a period of 5 years.

Facilities

The facilities simulated here include tank batteries taken from Stokes et al.,[19] comprising large centralized facilities and smaller ones based on the number of tanks, plus wellhead only sites. The smaller tank batteries are representative of older facilities which typically include one or a few wellheads, separation equipment and tanks on the same pad. On the other hand, the centralized tank batteries include larger numbers of tanks and typically do not have wellheads on the pad, rather they process output from multiple wellhead only sites located at pads in close proximity. The types of facilities here simulated are the first difference compared to previous simulations,[11,12] making the simulation more representative of facilities in the field, particularly the Permian basin and allowing to test the effect of having certain LDAR programs present only at facilities with larger potential to emit. Details on equipment and component counts at each facility are described in the Supporting Information (SI) Section S.1.

Emission measurements

One of the most important parameters in LDAR models is the emission distribution, which needs to be representative of the conditions in the field, for example by including high emitters. Here, the approach was not to fit a distribution to the data and rather sample from measurements, as done in Zavala-Araiza et al.[14] and Allen et al.[20] Only non-routine emissions were simulated as the objective was to estimate emission reduction.

Here, two different sources of emissions based on field data were combined to have a representative emission distribution of the Permian basin. The first dataset came from studies using close range inspections (OGI cameras or method 21) from Allen et al.,[7] Bell et al.[21] and Kuo et al.,[22] as described by Kemp et al.[13] with the addition of data from Pacsi et al.[23] These studies were chosen as they have information of the equipment where each emission originated from, which was used to randomly assign emissions in this study from that equipment category, for example a component at a separator will sample from the emissions originating from separators from the combined datasets. The second dataset was from Permian basin flyovers from Bridger Photonics, whose distribution is shown in Figure 1 and was also disaggregated by equipment. This dataset includes measurements that are higher than 26 kg/hr, which is a threshold typically used to refer to high-emitters (also referred to as super-emitters).[14] Bridger Photonics uses a continuous wave LiDAR measurements and has been described and evaluated by Johnson et al.[24] and Conrad et al.[25] From this dataset, only the emissions where operators confirmed that the source was non-routine, after following-up, were included in the distribution. Sensitivity analysis S0 was performed by adding to the distribution of close range inspections data from ERG[26] and Ravikumar et al.,[27] as described by Kemp et al.,[13] and assigning emissions randomly from a combined distribution, independently of which equipment the data came from, except for tanks and flares where the data comes from the flyover distribution.

Emissions from the studies using close range inspections were added to the flyover dataset, which surveyed 1251 facilities, to account for the emissions below the detection threshold of the aerial flyovers. The first step to integrate these measurements was to average the percentage of sites with emissions in each close range study weighting the average based on the number of sites surveyed in each study. The weighted average resulted in 71% of sites having leaks from the close range inspection datasets. This value carries uncertainty as it aggregates field studies performed in different locations, with different types of facilities and at different times, thus, this value was varied in sensitivity analyses S1 and S2 to be 91% and 51%, respectively, to assess the effect of this parameter on the emission reduction results. Additional details on how emissions from the close range inspection were combined to the flyover dataset are detailed in SI Section S.2.

Leak generation rates

Transitions between leaking and non-leaking states were simulated with the same equations (Eqs. 1-3) as in the MEET model.[17,18] Non-routine emissions from tanks and flares were also simulated with these equations, and they were modeled at the equipment level, whereas emissions from the other equipment were modeled at the component level.

$$t_{next\ leak\ starts} = t_{previous\ leak\ stops} - MTBF * Ln(1 - random\ number) \qquad \text{(Eq. 1)}$$

$$t_{leak\ stops,\ \ no\ LDAR} = t_{leak\ start} - MTTR * Ln(1 - random\ number) \quad \text{(Eq. 2)}$$

$$MTTR = \left(\frac{pLeak}{1-pLeak}\right) * MTBF \quad \text{(Eq. 3)}$$

Where pLeak is the fraction of a particular component or equipment that are observed to be emitting in a given point in time during field studies. Mean Time Between Failures (MTBF) is the average time it takes for a new leak to emerge and is estimated based on field data; this variable is referred to as leak generation rate in FEAST and LDAR-Sim. Mean Time To Repair (MTTR) represents the time that leaks stop emitting outside LDAR inspections, and is a parameter referred to as null repair rate in FEAST and LDAR-Sim.[11,12] MTTR is included in these types of models as it keeps the number of leaks relatively steady at the value of pLeak, when averaged over a long period of time and over multiple simulations, in scenarios that do not have LDAR programs.

From the variables in Eqs. 1-3, pLeak can be directly obtained from surveys, MTBF is typically estimated based on surveys, and MTTR is then estimated based on Eqn. 3. The way that MTBF is typically estimated is to count the number of components of a particular kind that are leaking on a given LDAR survey and then divide the total time those components were operating in between LDAR surveys by the number of leaks, to arrive at the average time to leak.[12] The MTTR and MTBF parameters for component type of leaks were taken directly from the MEET model, while MTTR and MTBF for emissions from tanks and flares were estimated using the same approach as components, based on the time between the first Bridger flyover and the second one. Because some sites had OGI inspections in between the aerial surveys, if a site had detected emissions during an OGI inspection (some tanks were found to be emitting) those findings were also counted in the number of emissions in the time frame, as they were repaired before the second Bridger flyover. The pLeak value used for tanks was from the first aerial surveys as this is the baseline. For flares, the pLeak was taken from aerial surveys from the Environmental Defense Fund's PermianMap,[28] which reports that 10% of tanks in the Permian have flares that are malfunctioning, including half of the malfunctioning as unlit. At the beginning of the simulation the pLeak number of each component or equipment was assigned to determine which components and equipment were emitting initially. Table 1 shows the values of pLeak, MTBF and MTTR used for the base case simulations. MTBF and MTTR are mean values that will lead to temporal variability of individual leaks based on Eqs. 2-3. Figure S4 shows a distribution of times for leak onset and times before leaks stop in the absence of LDAR to illustrate the temporal variation.

Table 1. Parameters used in base case scenarios for transition between leaking and non-leaking states.

Component/equipment	pLeak	MTBF [days]	MTTR [days]
Valves	0.00191	191132	366
Connectors	0.000665	548968	365
OEL	0.00646	56536	368
PRV	0.0272	13398	375
Flanges	0.000665	548968	365
Other	0.000665	548968	365
Tanks	0.046	1515	73
Flares	0.1	1435	159

Leak generation rates and null repair rates (MTBF and MTTR) are among the parameters with the most uncertainty and also ones that affect outcomes the most.[12,13] To account for the uncertainty in their values, Fox et al.[12] suggest performing sensitivity analyses varying these parameters. In this work sensitivity analyses were constructed based on empirical data on duration of emissions from Cusworth et al.,[8] which surveyed facilities multiple times in the Permian in 2019 for a month and a half period to assess persistency of high emitters. To be able to use Eqs. 1-3, the traditional approach is to get pLeak from surveys, estimate MTBF from survey data and calculate MTTR using Eq. 3. Here, the approach was to first estimate MTTR values based on empirical data on emission duration from Cusworth et al.,[8] followed by calculation of MTBF values using Eq. 3 and the pLeak values from surveys. A description of how these parameters were derived is detailed in SI Section S.3., and the values varied across the sensitivity analyses are shown in Table 2.

Table 2. Parameters varied in sensitivity analyses and base case simulations.

<table>
<tr><th>Set of simulations</th><th>Close range inspection datasets, which are then combined with the flyover dataset</th><th>Fraction of sites with emissions from close range inspections, when combining close range and flyover datasets at each Monte Carlo iteration</th><th>pLeak*</th><th>MTBF [days]*</th><th>MTTR [days]*</th></tr>
<tr><td>Base case</td><td>Allen et al.,[7] Bell et al.,[21] Kuo et al.,[22] Pacsi et al.[23] †</td><td rowspan="2">0.71</td><td rowspan="7">Tanks = 0.046
Flares = 0.1</td><td rowspan="4">Tanks = 1515
Flares = 1435</td><td rowspan="4">Tanks = 73
Flares = 159</td></tr>
<tr><td>Sensitivity analysis S0</td><td>Allen et al.,[7] Bell et al.,[21] Kuo et al.,[22] Pacsi et al.,[23] ERG,[26] Ravikumar et al.[27] ‡</td></tr>
<tr><td>Sensitivity analysis S1</td><td rowspan="5">Allen et al.,[7] Bell et al.,[21] Kuo et al.,[22] Pacsi et al.[23] †</td><td>0.91</td></tr>
<tr><td>Sensitivity analysis S2</td><td>0.51</td></tr>
<tr><td>Sensitivity analysis S3</td><td rowspan="3">0.71</td><td>Tanks = 103.7
Flares = 45</td><td>Tanks & flares = 5</td></tr>
<tr><td>Sensitivity analysis S4</td><td>Tanks = 207.4
Flares = 90</td><td>Tanks & flares = 10</td></tr>
<tr><td>Sensitivity analysis S5</td><td>Tanks = 622.2
Flares = 270</td><td>Tanks & flares = 30</td></tr>
</table>

* All sets of simulations use the pLeak, MTBF and MTTR parameters specified in Table 1 for: valves, connectors, OEL, PRV, flanges and other components. † Emissions assigned based on equipment type from measurements, for all sources. ‡ Emissions assigned independently of equipment type from measurements, except for tanks and flares.

LDAR scenarios

In this work, multiple combinations of technologies with various levels of detection thresholds were used. Initially the simulations were performed using the base case parameters. In addition, all scenarios were performed again for the various sensitivity analysis (S0-S5).

The first scenario was no LDAR, that serves as a baseline to which the LDAR scenarios were compared to in order to estimate reduction; the first year of each simulation was not included when estimating reduction, only years 2-5 were included. Scenarios with only OGI surveys were included with frequencies of 1x (1 time a year), 2x, 4x, 6x and 12x, with a detection threshold taken from Ravikumar et al.[29] assuming a distance of 1.5m. The 4x OGI scenario corresponds to the survey frequency proposed by EPA for new regulations,[30] and was used as reference.

Aerial scenarios were simulated in combination with OGI by having in a given year one scheduled OGI inspection at all facilities plus 1x-11x aerial surveys. For example, 1x aerial + 1x OGI means two inspections a year 6 months apart from each other, one using aerial and one using OGI. The detection thresholds simulated for aerial were: 2, 5, 10 and 25 kg/hr. Scenarios with combinations of satellite + aerial + OGI were included by having the same scenarios described for aerial + OGI, plus the satellite coverage. For satellites, two frequencies that cover all facilities were included, daily revisit and weekly revisit; while these revisit frequencies might not be currently available multiple satellite constellations are being planned which will enable them.[31,32] The two satellite detection thresholds included were 50 and 100 kg/hr, which are within the range of what Jacob et al.[31] described as the capabilities of point source monitoring satellites. Scenarios with satellites + 1x OGI and no aircraft were also included. Satellite detection of emissions is diminished by cloud cover, and details of how their effect were implemented in the model are detailed in SI Section S.4.

Continuous monitoring were included by using networks of sensors: one or less than one sensor per site, combined with OGI 1x. Based on simulated data from Chen et al.,[33] it was assumed that these networks of sensors were able to detect emissions of 5 kg/hr and 10 kg/hr within 1 week of emission onset (uniform distribution, sample randomly the number of days to detection). Additional scenarios were included that add satellite detection in parallel with of the networks of continuous monitors + OGI.

Continuous monitors were also simulated as being present on a site basis combined with OGI 1x. It was assumed that all sites had sensors and emissions were detected within 1 day of onset. The detection thresholds simulated were 0.2, 2, 5 and 10 kg/hr. Additional scenarios were included that add satellite detection on top of the continuous monitors + OGI.

Finally, a tiered approach was used with site level continuous monitors present only on tank batteries (priority sites), which have tanks and/or flares, since they are the most common sources of super-emitters, while wellhead only sites (non-priority sites) were not assigned continuous monitors. The priority sites had continuous monitors + 1x OGI, while the non-priority sites had scenarios of 1x OGI, and 1-5x aerial + 1x OGI. Scenarios with satellites in parallel with the described sensors were also included. Table S2 shows in detail the scenarios simulated.

Repair times.

Once leaks were found by the detection technologies, they were scheduled for repair. For OGI inspections, repair times were selected at random between 1 and 30 days after inspections. For aerial inspections, repair times were randomly selected between 1 and 30 days after the final report was received, which was received 8-14 days after the first flyover. Leaks found with continuous monitors and satellites were assumed to be repaired within 7 days and 2 days, respectively, chosen at random from a uniform distribution. When surveys from different technologies coincide on the same day (e.g. satellite and aircraft), and if the leak was found by more than one technology, the lowest repair time was chosen.

Scenarios were performed by having leaks detected by satellites and continuous monitors, repaired within 30 days, as opposed to sooner, to compare the effect of repair times on the emission reduction. In total, based on the permutations of detection threshold and repair times, 566 simulations were ran for the base case, in addition to 566 for each of the sensitivity analysis S0-S5 (See tables 2 and S2 for details of simulations ran). Technologies such as aerial, continuous monitors and satellites need a follow up to find the exact cause of the leak and repair it, and while being at the site operators might survey parts or the entire facility to find additional potential leaks. Here, it was assumed that only the emissions found in the original surveys were repaired as a conservative approach.

LDAR simulation results

The following sub-sections focus on particular combinations of technologies, repair times and site visits. SI section S.6. analyzes the effect on emission reduction of including vs not including emissions from flares; given that there is no significant difference on a relative or absolute basis, results including emissions from flares are reported in following sub-sections. SI section S.7 assesses the change in reduction of the sensitivity analyses compared to the base case simulations; at it shows that the most sensitive parameters are the leak generation and null repair rates. Results reported in following sub-sections include base case and sensitivity analysis S3 simulations to contrast results since they have the longest and shortest duration of high-emitters, respectively.

Combinations of satellite, aerial and OGI sensors

Figure 2a shows the emission reduction of aerial surveys with 10 kg/hr detection threshold and yearly OGI. As has been reported previously,[13] emissions decrease with increasing frequency of inspections. However, the benefit of additional inspections has diminishing returns. This figure also shows a tiered approach with daily satellite revisits with a detection threshold of 50 kg/hr plus the aerial and OGI surveys. The addition of satellite-based detection further reduces emissions considerably, as all scenarios with satellite lead to more reductions than even a scenario with 12x OGI. This reduction occurs because of the skewness in the emission distribution, where high emitters account for a disproportionate share of total emissions, and by having a strategy to prioritize detection and repair of the high-emitters. Figure 2b shows the same LDAR programs under sensitivity analysis S3 (shortest duration of emission). Here the data also shows that a tiered approach leads to further reductions than the OGI only or aerial + OGI.

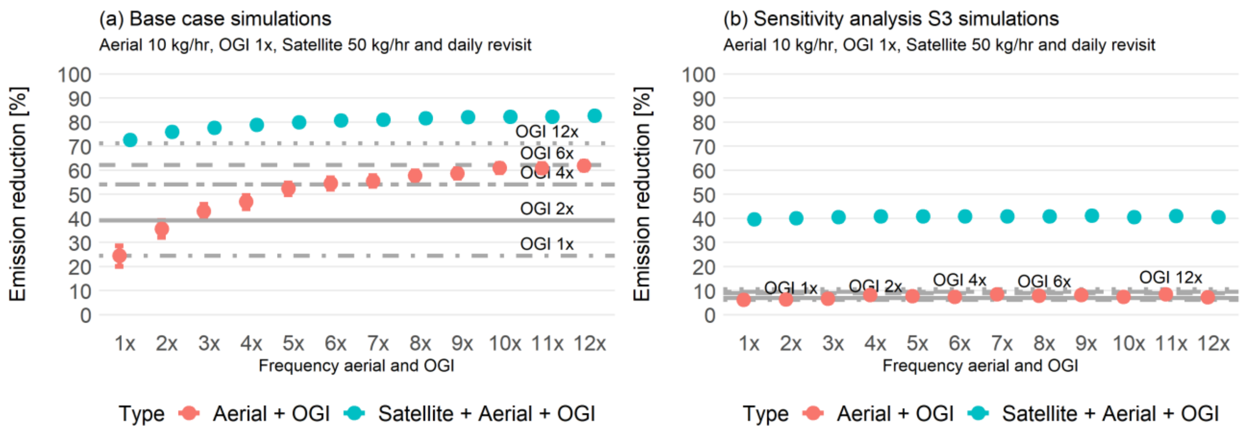


Figure 2. Emission reduction of LDAR scenarios with aerial + OGI and satellite + aerial + OGI for (a) base case (long duration of high-emitters) and (b) sensitivity analysis S3 (short duration of high-emitters) simulations. Horizontal lines indicate the reduction of OGI only LDAR programs. The horizontal axis represents frequency of inspections for aerial and OGI. 1x for aerial + OGI is equal to 1x OGI, while 1x for satellite + aerial + OGI is equal to satellite + 1x OGI.

Effect of aerial detection threshold

Having a lower detection threshold helps aerial technologies achieve higher reductions in scenarios with long-duration of high emitters, particularly as the number of flyovers per year increases (Figure S8). On the other hand, in scenarios with short duration of high emitters the detection threshold of aerial technologies is not substantial. In scenarios of both short and long duration of high-emitters, significantly higher reductions can be achieved with tiered approaches that include frequent inspections with satellites in parallel to the aerial + OGI surveys, as opposed to more frequent aerial surveys with a lower detection threshold.

Effect of satellite frequency and detection threshold

Figure S9 shows the reductions of LDAR programs that include satellite, aerial and OGI technologies, with variations in the satellite revisit times and detection thresholds. In scenarios with long duration of high emitters (S9a) all combinations perform better than 4x OGI and some scenarios better than 12x OGI. The highest reduction is achieved by 50 kg/hr and daily revisits, and lowest by 100 kg/hr and weekly revisits. At lower numbers of aerial surveys, 50 kg/hr and weekly revisit leads to higher reduction than 100 kg/hr and daily revisit, while in scenarios with more frequent aerial surveys, 100 kg/hr and daily revisits leads to higher reduction. On the other hand, in scenarios with short duration of high emitters (Figure S9b) frequency is the most important parameter, with 50 kg/hr and daily revisits having the highest reduction, followed by 100 kg/hr and daily revisits. All scenarios of satellite detection lead to higher emissions than OGI 12x, however the reduction is significantly higher for those with daily revisit than weekly revisit.

Combinations of continuous monitors with satellite, aircraft and OGI sensors

Networks of continuous monitoring sensors

Emission reductions for scenarios with networks of continuous monitor sensors + 1x OGI are shown in Figure 3. Given that emissions can be found on a continuous basis, the time that larger leaks are emitting is reduced significantly, and higher reductions than OGI 4x and even OGI 12x can be achieved, independently of the presence of satellites. When the duration of high-emitters is shorter (Figure 3b), networks of continuous monitoring sensors + OGI with/without satellites still perform better than OGI 12x, however the combinations with daily revisits of satellite perform better than those without satellites or with satellites and weekly revisits. This differences arise because the time assumed for detection of emissions with networks of sensors were within 7 days, while the mean duration of high-emitters was 5 days in the sensitivity analysis S3 scenarios.

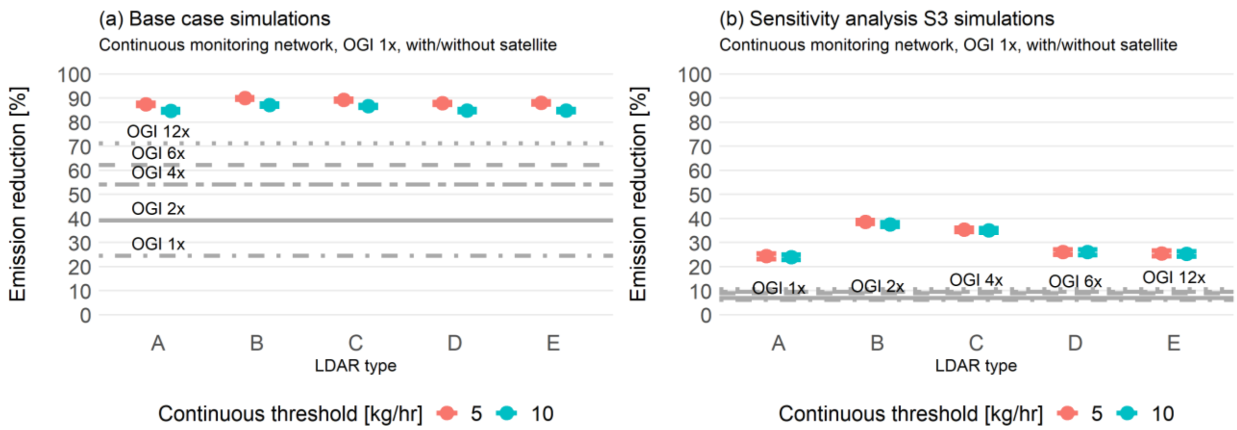


Figure 3. Emission reduction of LDAR scenarios with continuous monitoring networks + OGI and satellite + continuous monitoring networks + OGI for (a) base case (long duration of high-emitters) and (b) sensitivity analysis S3 simulations (short duration of high-emitters). LDAR type A is no satellite. LDAR type B is satellite with 50 kg/hr and daily revisits. LDAR type C is satellite with 100 kg/hr and daily revisits. LDAR type D is satellite with 50 kg/hr and weekly revisits. LDAR type E is satellite with 100 kg/hr and weekly revisits. Horizontal lines indicate the reduction of OGI only LDAR programs.

<u>Site level continuous monitoring</u>

Scenarios with site level continuous monitoring sensors across all sites result in slightly greater but comparable reductions on emissions than networks of sensors (Figure S10). Similarly, reductions achieved by having only continuous monitoring on priority sites are comparable to those having them across all sites (Figure S11), suggesting that strategies that have continuous monitoring sensors located only at facilities with equipment prone to be high-emitting are equally effective. All scenarios with site level continuous monitors achieve higher reductions than the OGI only inspections, including 12x OGI.

Effect of repair times

Some simulations were performed assuming that all leaks were repaired randomly within 30 days of being found, independently of their magnitude. Figure 4 compares the effect that repair times have on emission reduction for scenarios with continuous monitors at priority sites, satellites and 1x OGI. All scenarios achieve larger reductions than 12x OGI, under both long duration of high-emitters (Figure 4a) and short duration of high-emitters (Figure 4b). However, repairing larger emissions quicker can lead to significantly more reductions, the effect is even more pronounced in scenarios with short duration of high-emitters. For satellite + aerial + OGI, many of the scenarios have more reduction than OGI 4x, however most reductions tend to be below or near those of OGI 12x (Figure S12).

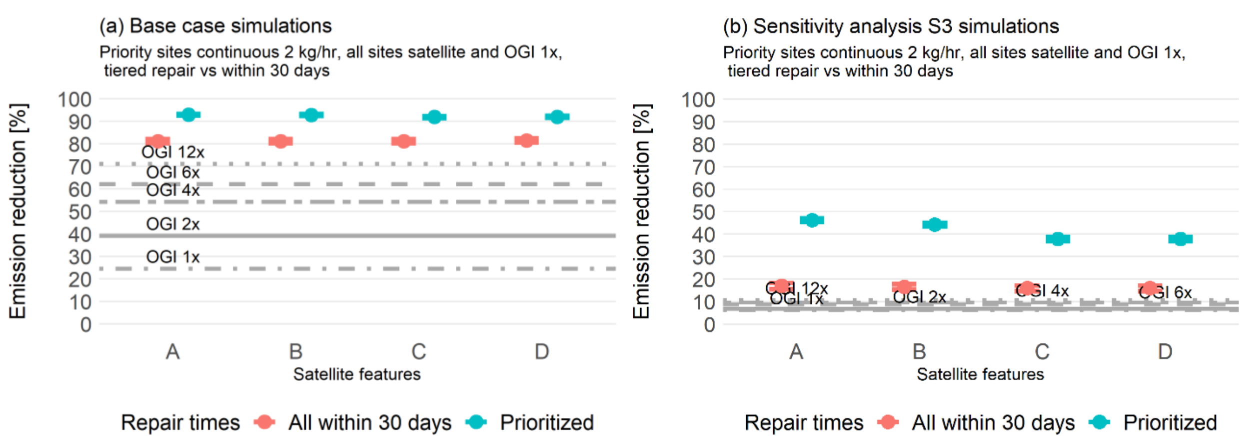


Figure 4. Emission reduction of LDAR scenarios with continuous monitors at priority sites, satellites and OGI, comparing repair times for sources detected with satellites and continuous monitors prioritized vs. all within 30 days for (a) base case (long duration of high-emitters) and (b) sensitivity analysis S3 (short duration of high-emitters) simulations. LDAR type A is satellite with detection threshold of 50 kg/hr and daily revisit. LDAR type B is satellite with detection threshold of 100 kg/hr and daily revisit. LDAR type C is satellite with detection threshold of 50 kg/hr and weekly revisit. LDAR type D is satellite with detection

threshold of 100 kg/hr and weekly revisit. Horizontal lines indicate the reduction of OGI only LDAR programs.

Number of LDAR Hours Required

In addition to evaluating emission reduction, the time needed to carry out the LDAR programs was considered in the analysis, including ground inspection, administrative and driving hours. The approach is similar to the one described by Sridharan, et al.[34] and is detailed in SI Section S.11. Figure 5 shows the number of hours required in each LDAR program normalized by the hours needed in the OGI 4x program. All simulations in the base case scenarios (Figure 5a) using advanced detection technologies lead to less time needed than OGI 2x, suggesting that many LDAR programs can achieve high emission reductions and be less labor intensive. On the other hand, when the duration of high emitters is short, the number of site visits increases significantly (Figure 5b). For sensitivity analysis S3 all scenarios of LDAR with aerial + OGI or satellite + aerial + OGI require less hours than 4x OGI, however those that incorporate continuous monitoring require more hours than OGI 4x. The detection threshold of continuous monitors is inversely proportional to the LDAR hours required, as those with lower detection threshold require more time (Figure S13). Figure S14 shows the number of site visits required for sensitivity analysis S4 and S5 scenarios. The duration of high-emitters is a sensitive parameters for both the LDAR required hours and for emission reduction (Figures 5 and S14).

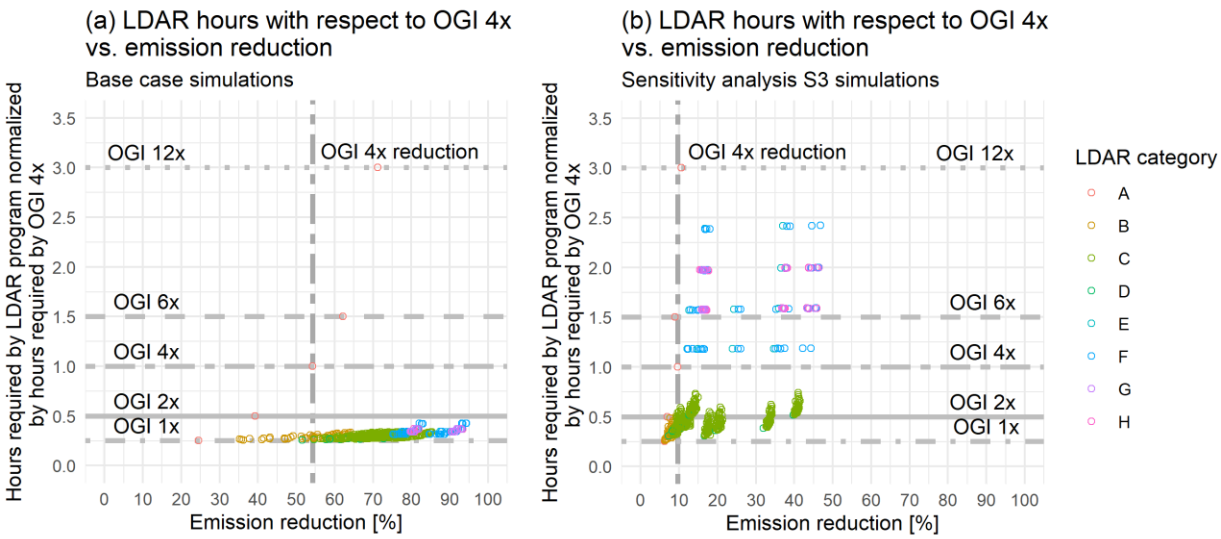


Figure 5. Number of hours required by LDAR programs normalized by the hours required by OGI 4x vs. their emission reduction for (a) base case (long duration of high-emitters) and (b) sensitivity analysis S3 (short duration of high-emitters) simulations. The data points are colored by LDAR category: "A" = OGI, "B" = Aerial + OGI, "C"= Satellite + aerial + OGI, "D" = Satellite + OGI, "E" = Continuous + OGI, "F" = Satellite + continuous + OGI, "G" = Satellite + continuous at priority sites + OGI, "H" = Satellite + continuous at priority sites + aerial at non priority sites + OGI. Horizontal lines indicate the number of visits of OGI only LDAR programs. The vertical line indicates the reduction of OGI 4x. Each data point corresponds to one scenario in a particular LDAR category, with differences in detection threshold, frequency of inspections and repair times.

Model limitations and implications

One assumption of LDAR models is that the leak generation rates are constant throughout the simulation, due to limited data on leak recurrence, in particular for high-emitters. Variations in times of leak reoccurrence or absence of leak reoccurrence might occur due to equipment replacement or preventive maintenance. These practices were not implemented in this work, however they would be expected to achieve further emission reductions that those reported here. While information on leak recurrence is lacking, recent empirical studies suggest that effective reductions can be achieved by LDAR in the oil and gas production sector.[27,35,36] There is also lack of data on the temporal characteristics of high-emitters, which is a very sensitive parameter. Future work should focus on obtaining information on duration of high-emitters and on root-cause analysis, which will be particularly relevant when doing LDAR modeling coupled with a process based simulator that includes routine emissions and with a finer simulation temporal resolution. Emissions from gathering pipelines were not included in this work since this model does simulations for individual facilities and not over a particular geographic area coupled with atmospheric dispersion models. Recent evidence suggest that this source can be significant in some regions,[8,37] and novel technologies, in particular remote sensing platforms, are helpful to detecting these emissions. Recent studies show larger emissions than the distribution from non-routine emissions in the Permian here used, but don't distinguish if they are leaks or routine short-duration emissions;[8,16] if some of these larger emissions were unintended, the distribution would be more skewed, leading to even more reductions with the combinations of advanced technologies.

LDAR models like the one used in this work can effectively compare LDAR programs on a relative basis and have large uncertainty on predicting absolute emission reductions given the uncertainty in certain parameters. However, after varying key parameters in sensitivity analyses, consistent results evidence that LDAR strategies that combine detection technologies with a focus on finding and fixing the largest emissions quickly while having less frequent OGI inspections lead to greater reductions than strategies with only OGI surveys at intervals of months. Multiple combinations of technologies achieve larger reductions than OGI 4x or even OGI 12x, giving operators multiple options to choose from. These results are specific for oil and gas production basins that have large numbers of high-emitters, and could differ in basins with low levels of high-emitters.

Associated Content

Supporting Information

Detailed data on simulations conditions and additional graphs.

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Notes

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