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Large-Scale Controlled Experiment Demonstrates Effectiveness of Methane Leak Detection and Repair Programs at Oil and Gas Facilities

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Abstract

The importance of reducing methane emissions from oil and gas operations as a near-term climate action is widely recognized. Most jurisdictions around the globe using leak detection and repair (LDAR) programs to find and fix methane leaks. In this work, we empirically evaluate the efficacy of LDAR programs using a large-scale, bottom-up, randomized controlled field experiment across ~200 oil and gas sites in Canada. We find that tanks are the single largest source of emissions, contributing to nearly 60% of total emissions. The average number of leaks at treatment sites that underwent repair reduced by ~50% compared to control sites. Although control sites did not see a reduction in the number of leaks, emissions reduced by approximately 36% suggesting potential impact of routine maintenance activities to find and fix large leaks. By tracking tags on leaking equipment over time, we find a high degree of persistence – leaks that are repaired remain fixed in follow-up surveys, while non-repaired leaks remain emitting. We did not observe any significant growth in emission rate for non-repaired leaks, suggesting that any increase in observed leak emissions following LDAR surveys are likely from new leaks. Vent emissions reduced by 38% without a significant reduction in the average number of vents across control and treatment sites, showing the importance of both anomalous vents and temporal variations in vent emissions. Our results show that a focus on equipment and sites that are prone to high emissions such as tanks and oil sites are key to cost-effective mitigation.

Significance Statement

Mitigating methane emissions from the oil and gas sector is a key component of near-term climate action. Although widely used, the effectiveness of policies such as leak detection and repair (LDAR) surveys have not been demonstrated in the field. Here, we present results from a large-scale controlled experiment across ~200 oil and gas sites to evaluate the emissions reduction effectiveness of LDAR surveys. This study provide insight on how methane emissions evolve over time using periodic LDAR surveys. We find that leaks are persistent, repairs are effective long-term, and that significant emissions reductions can be achieve by focusing on equipment and sites prone to high emissions. Large sample size allows for insights to be translated to other O&G producing regions.

Main Text

Introduction

Methane (CH_4) is a short-lived but highly potent greenhouse gas (GHG) with a global warming potential (GWP) 28 times that of carbon dioxide (CO_2) over 100 years [1]. If global energy sector methane emissions were its own country, it would be the third largest emitter in the world, behind only China and the US. The recently concluded 26th Conference of Parties saw over 100 countries pledging to reduce methane emissions by 30% by 2030 [2]. In particular, emissions from oil and gas (O&G) operations contribute to 14% of all methane emissions globally [3], [4]. Most jurisdictions around the world use periodic leak detection and repair (LDAR) surveys to find and fix methane leaks in the O&G sector [5], [6].

Studies across Canada and the U.S. have consistently demonstrated significant underestimation of methane emissions in official GHG inventories [7]–[11]. In the Red Deer region in Alberta, recent studies have found measured emissions to be 15 – 18 times higher than those directly reported to the Alberta Energy Regulator's (AER) [12], [13]. This discrepancy is attributed to incomplete reporting requirements and the heavy-tailed emission distribution commonly observed across oil and gas facilities [7], [8], [13]–[17]. These high-emitters have significant spatiotemporal uncertainty, creating challenges to their timely detection both for estimating accurate emissions inventory and mitigation efforts [18]–[21].

Detailed component-level emissions data can improve our understanding of the characteristics and distribution of emission sources. However, collecting such data can be time-consuming and labor intensive. Large-scale studies of methane emissions from the upstream of the oil and gas sector are typically done at the site-level through aircraft and mobile laboratory measurements, or at the regional level using mass-balance approaches [12], [13], [22], [23]. Though such methods can survey a large number of sites in a short time, they have higher detection limits and cannot directly identify emission sources [24]. As a result, these studies seldom offer insights into emitting components or the root-cause of emissions [25]. Yet, an analysis of the time evolution of methane emissions requires component-level data to determine persistence, mean time to failure, and other critical parameters that affect methane emissions. Furthermore, top-down aerial methods cannot differentiate emissions between leaks and vents. In our definition, leaks are non-operational and unintentional, whereas vents are operational and intentional. Since an LDAR program aims to reduce leaks, detailed data on leaks and vents can help estimate the effectiveness of the program.

Most field studies of methane emissions from oil and gas facilities using new technologies such as aircraft and satellite provide ‘snap-shot’ measurement data – while detailed in spatial extent, they do not shed light on temporal variations in emissions [12], [26]. This is critical as recent measurements have observed significant differences in emissions across seasons, time of day, and other temporal variables [27], [28]. Furthermore, only one recent study has empirically demonstrated emissions reductions from regulatory LDAR programs with data from a small number of facilities [29].

In this work, we present results from a large-scale, randomized controlled trial of the effectiveness of LDAR surveys in reducing methane emissions using component-level, repeat surveys from approximately 200 oil and gas sites across 18 operators in Alberta, Canada. This work brings together several critical aspects of methane emissions for the first time to shed light on the temporal evolution of emissions under LDAR programs. First, random site selection without the knowledge of the operators involved avoids the ‘coalition of the willing’ challenge associated with bottom-up, component-level studies that typically require operator consent for site access. Second, the large sample size for a component-level randomized study ensures representativeness of oil and gas facilities and therefore, broad applicability of insights. Third, differentiating control and treatment sites allows differentiation of emissions reductions associated with voluntary inspection and maintenance activities from that of an LDAR program. Fourth, emissions tracking through repeat surveys over the course of 12 months provides the first scientific data on emissions growth rate, persistence of leaks, and the effectiveness of the repair process. Findings from our study will answer long-standing scientific questions on methane emissions as well as help regulators identify the most effective emissions mitigation policies.

Results and Discussion

We selected approximately 200 representative sites in the Red Deer region of Alberta and divided into four groups – three treatment groups and one control group. The three treatment groups, with approximately 45 sites each, were surveyed annual, bi-annually, and tri-annually, respectively. The sites in the control group were surveyed annually. Surveys were conducted using optical gas imaging technology, recording all methane emissions on site include vents. Emissions are quantified using quantitative optical gas imaging technology (see Methods and SI section S.1). At each treatment site, the results of the LDAR survey were provided to the site operator, with the expectation that repairs would be conducted prior to the next survey on that site. At control sites, the operator was not notified about the results of the LDAR surveys but were free to undertaken routine maintenance activities. The initial baseline survey of all sites was conducted in fall 2018 and the final survey was conducted a year later, in fall 2019 (see SI section S.1.2).

Vent emissions, on average, constitute a disproportionate share (> 69%) of total methane emissions.

Figure 1 compares component-level emissions data between the initial and final surveys in fall 2018 and fall 2019, respectively. Figure 1(a) and Figure 1(b) show the cumulative distribution of component-level emissions as a function of rank-ordered cumulative number of emitters. Emitters are disaggregated by six major component types as well as by leak and vent emissions. We found 1025 emitters in the initial survey in 2018 and 1004 emitters in the final survey in 2019. The average emission rate reduces by 41% from 49 kg CH_4/d (95% CI [41 - 62]) to 29 kg CH_4/d (95% CI [24 - 38]). The decrease in average emission rate can be attributed to reduction in the number of large emitters. In 2018, there are 94 large emitters emitting >100 kg CH_4/d, contributing to 74% of total emissions. In 2019, the number of large emitters emitting >100 kg CH_4/d drops to 65 emitters, contributing to 62% of total emissions. In addition, 90% of the emissions come from components emitting >31 kg CH_4/d in 2018 and >16 kg CH_4/d in 2019 – these correspond to only 22% and 27% of emitters in 2018 and 2019, respectively. Such skewed component-level emissions distribution have been observed in several recent studies [13], [17], [30]. Overall, the highest-emitting 5% of emitters contribute to 56% of total emissions in 2019, compared to 62% in 2018. Among the top 5% of emitters in 2018 (n = 51), the most common emitting component is a tank related open-ended line (n = 22), contributing to 30% of total emissions. The distribution is similar in 2019 – tank related open-ended lines (n = 26) contributed to 31% of total emissions.

The inset bars in Figure 1(a) and Figure 1(b) show the fractional make-up of emitters and emissions across major component types. Flange/connector, pneumatics, and valves are the most common emitting components, accounting for nearly 75% of all emitters. However, they only contribute to 33% of total emissions in 2019. On the other hand, components such as thief hatch and tank related open-ended line, despite accounting for only 14% of total emitters, are responsible for 47% of total emissions in 2019. Overall, tank related emissions – both leaks and vents – together contribute a significant fraction of total methane emissions (58%) and represent opportunities for specific monitoring and mitigation action.

The inset pie charts show the relative contributions of leaks and vents to total emissions. Vents (including anomalous vents) contribute to the majority of total emissions – 69% in 2018 and 76% in 2019. The increase in contribution from vents in 2019 is a result of mitigation actions taken to reduce leaks between 2018 and 2019. Total emissions reduced by 42% between 2018 and 2019. Disaggregating between leaks and vents, we find that total leak emissions reduce by 55% and total vent emissions reduce by 38%. The results here show that vents are a significant contributor to total emissions that are not directly addressed by LDAR programs. However, LDAR programs help bring anomalous vents to the attention of the operator potentially increasing their effectiveness beyond conventional leak mitigation efforts.

Figures 1(c) and Figure 1(d) compare the changes in emission-size distribution of leaks and vents between 2018 and 2019. There are 541 leaks in 2018 and 568 leaks in 2019. Even though the number of leaks found in the two surveys are similar, the average leak emission rate decreases by 59%, from 29 kg CH_4/d in 2018 (95% CI [20 - 43]) to 12 kg CH_4/d in 2019 (95% CI [10 - 17]). The decrease is mainly due to the reductions from high-emitting leaks associated with repair activities – there are 22 leaks that emit >100 kg CH_4/d and contribute to 71% of total leak emissions in 2018. By comparison, there are only 12 leaks emitting over 100 kg CH_4/d, contributing to 42% of total leak emissions in 2019. Total leak emissions from these large emitters reduced by 73% between surveys. As a result, the contribution of the top 5% of leaks to total leak emissions drops from 74% in 2018 to 57% in 2019 (Figure 1(a) and Figure 1(b)).

There are 484 vents in 2018 and 436 vents in 2019. While the counts of vents decrease by 10% between surveys, the average vent emissions rate decreases by 32%, from 73 kg CH_4/d (95% CI [58 - 96]) in 2018 to 50 kg CH_4/d (95% CI [40 - 71]) in 2019. Similar to leaks, reduction in vent emissions mainly come from large emitters. The number of vents that emit >100 kg CH_4/d decreases from 72 to 53 with corresponding emissions reduction of 43%. Although we cannot attribute reduction in vent emissions to any operator-specific action, we hypothesize several potential causes: 1) some vents are anomalous and are fixed by operators as part of routine maintenance; and 2) some vents are episodic and thus, not detected during the fall 2019 visit, or 3) some vents were addressed with process changes, equipment improvement, or targeted removal due to notification in LDAR campaign. Leaker emission factors across the six component types and five surveys are provided as tables in the supplementary information (see SI section S2).

Tanks are the single largest source of methane emissions, contributing to 58% of total emissions in 2019.

Figure 2 shows the distribution of emissions by major component types and tank relation in 2018 and 2019. Across all components, average emissions reduce between 35% and 84% from 2018 to 2019. Even though the average emission from non-tank related open-ended line increases from 32 kg CH_4/d (95% CI [25 - 47]) to 53 kg CH_4/d (95% CI [36 - 78]), both the count of emitters and total emissions reduce by 61% and 37%, respectively. The highest-emitting component types are found on tanks – thief hatch and tank related open-ended lines, with an average emission rate of 80 kg CH_4/d (95% CI [45 - 138]) and 104 kg CH_4/d (95% CI [77 - 185]), respectively, in 2019.

Pneumatic devices, typically considered outside the scope of LDAR programs, emit 12 kg CH_4/d (95% CI [11 - 15]) on average in 2019, which represents a significant reduction from 44 kg CH_4/d (95% CI [29 - 73]) in 2018. The reduction in average emissions is driven by reduction from large emitters (>100 kg CH_4/d). The number of pneumatic devices that emits >100 kg CH_4/d decreases from 19 in 2018 to 4 in 2019 and their emissions reduced by 91%. Flanges and valves represent some of the most common component types that are prone to exhibit leaks from wear and tear or component failure, but do not contribute significantly to overall emissions. On average, flanges and valves emit 12 kg CH_4/d (95% CI [7 - 22]) and 14 kg CH_4/d (95% CI [8 – 27]), respectively. The contrast in average emission rate between high-emitting but relatively uncommon components and low-emitting but common components suggest potential opportunities in mitigation protocols that focus on sources most likely to exhibit high emissions.

Aggregating all tank related emissions across component types, we find that tanks contribute to 52% and 58% of total emissions in 2018 and 2019, respectively, despite only comprising 18% and 16% of total emitters. The disproportionate contribution from tanks is consistent with findings from recent studies and makes it a potential target for focused mitigation opportunities [27], [31], [32]. Furthermore, the average emission rate of tank-related emissions in 2019 is 105 kg CH_4/d (95% CI [81 - 165]), which is nearly an order of magnitude (7.5x) larger than the average emission rate from non-tank related emissions, 14 kg CH_4/d. Thus, detecting tank related emissions could likely be accomplished with technologies with higher leak detection thresholds compared to conventional OGI cameras, like remote sensing, fly-by, or drive-by surveys [33].

Emissions from oil sites and multi-well batteries, on average, are more than two times that of emissions from gas sites and single-well batteries, respectively.

Figure 3 summarizes site-level emissions across 148 oil and gas production sites that are measured on schedule (see SI section S.1.2). Average emissions at each site are disaggregated by leaks and vents, and further analyzed based on site type, production, and size. The designation of oil and gas sites are based on established definitions of the oil and gas facilities by the AER. In the 2018 survey, 21 sites do not have any emissions and another 27 sites only have vent emissions, which translates into 32% of total sites surveyed with no leak emissions. The percentage drops to 25% in 2019 survey with 9 zero-emission sites and another 28 vent-only sites. Compared to other site-level survey methods such as mobile ground labs and aircraft systems used in prior studies, the OGI technology has a lower detection threshold [25], [33]. This may explain why the percentage of non-emitting sites in our study is lower than that of recent site-level measurements in the US and Canada [22], [24].

In 2019, the top 5% of sites contribute to 35% of total emissions, emitting at least 595 kg CH_4/d. 90% of total emissions come from sites emitting > 87 kg CH_4/d. The average site-level emission reduces by 46% from 295 kg CH_4/d (95% CI [215 - 449]) in 2018 to 158 kg CH_4/d (95% CI [122 – 227]) in 2019. Vent emissions are the major contributor to total emissions for nearly every site type considered in this study. In 2019, vent emissions contribute to 62% - 87% of total emissions for each site type. In 2018, vent emissions contribute to 48% to 84% of total emissions for each site type.

We also compare the count of emitters on site. Oil MW and Oil MWPro sites have the most emitters per site - 12.4 (95% CI [6.5 – 19.3]) and 11.6 (95% CI [6.5 – 29.0]) respectively in 2019. Oil SW and Gas SW have the fewest emitters per site, 3.9 (95% CI [3.3 – 4.6]) and 2.9 (95% CI [2.4 – 3.5]), respectively. The average count of emitters per site of all sites decreases by 9%, from 5.7 (95% CI [4.8 – 7.2]) in 2018 to 5.2 (95% CI [4.4 – 7.1]) in 2019. Yet, average emissions across all sites decrease by over 40% between 2018 and 2019, indicating the impact of addressing high emitters on overall emissions reductions. Notably, Gas MW sites have the most significant decrease of 2.7 emitters per site, compared to Gas SW, Oil MW, and Oil SW sites, which all decrease by less than 1 emitter/site. The only site type that sees an increase in the number of emitters is Oil MWPro sites, increasing from 9.9 (95% CI [5.6 – 20.4]) emitters per site in 2018 to 11.6 (95% CI [6.5 – 29.0]) emitters per site in 2019. The reduction of count of emitters of each site type depends on both the treatment group the site is in and the corresponding repairing activities from the operators, which is further discussed later.

Emissions also vary significantly by type of resource produced and the size of the facility. In 2018, the average emissions from all oil production sites (Oil SW, Oil MW, and Oil MW Pro) is 336 kg CH_4/d (95% CI [236 - 484]), 36% more than the 247 kg CH_4/d (95% CI [134 - 600]) from gas production sites (Gas SW, Gas MW). Even though emissions from both oil and gas production sites reduce in 2019, emissions decrease more at gas production sites: a decrease of 61% at gas production sites, compared to 38% at oil production sites. As a result of the different rate of decrease, oil production sites (210 kg CH_4/d (95% CI [154 - 327])) emit 2.2 times that of gas production sites (96 kg CH_4/d (95% CI [63 - 170])) in 2019. Oil sites emit more than gas sites because they are typically associated with equipment such as tanks that are prone to be high emitters and are the largest single source of emissions in this study. Similarly, we find that multi-well batteries emit more than twice that of single well batteries on average in both surveys, potentially attributable to the complexity and higher activity factors associated with multi-well sites. Emissions from both oil and gas multi-well batteries reduce by 47% from 475 kg CH_4/d (95% CI [285 - 973]) to 254 kg CH_4/d (95% CI [182 - 365]). Correspondingly, emissions from both oil and gas single well batteries reduce by 46% from 219 kg CH_4/d (95% CI [148 - 327]) to 118 kg CH_4/d (95% CI [81 - 213]).

Gas MW sites see the highest emissions reduction of 72%, followed by Oil SW and Oil MW sites, both reducing by 49%. The decrease in site level emissions is driven by a few sites with large emissions reductions since the initial survey in 2018. For example, the top two Gas MW sites with the highest emissions reduction make up 75% of total emissions reduction across all Gas MW sites. The decrease in emissions mainly come from large emissions associated with tank level controllers and tank open-ended lines (e.g., candy cane vent) in the initial survey, which were not emitting during the final survey. Similarly, the top two Gas SW sites with the highest emissions reduction contribute to 63% of total emissions reductions across all Gas SW sites. While Oil MW sites have a small sample size that may not be representative of the site type, it follows the same pattern where the top two sites with the highest emissions reduction contribute to 84% of total emissions reduction across all Oil MW sites. The persistent difference between oil and gas sites in both emissions and the potential for emissions reductions suggest mitigation opportunities for policies that are directed at specific site types.

On a proportional loss rate based on energy production (see Equation (1)), sites emit 2.6% of total energy produced in 2019, in line with recent findings. For example, Chan et al.'s recent revision of methane emissions estimates from Alberta and Saskatchewan translate to an energy based proportional loss rate of 2.8% [11]. In general, there are fewer points of comparison with published studies as the typical practice in the literature has been to report on gas-based proportional loss rates (see SI section S.5 for gas-based PLR). The PLR_e of oil sites is 3.0%, approximately 60% more than that of gas sites at 1.9%. The higher PLR_e at oil sites can be attributed to the higher incidence of tanks and resulting higher emissions (Figure 3). Although MW batteries emit more methane, on average, than SW batteries, their PLR_e is significantly lower on account of high energy production – the average energy produced from MW batteries is nearly 5 times that of SW batteries. Thus, the PLR_e of MW and SW batteries are 1.8% and 4.1%, respectively. In line with several recent studies, we find a decreasing trend in proportional loss rates as production increases (see SI section S.5) [29].

Emissions comparison across the 18 operators shows significant variation based on asset portfolio. Operators with more oil sites exhibit higher average emissions. Moreover, even though operators have similar median site emissions, the average site emissions vary by an order of magnitude. This discrepancy points to the impact of high-emitting sites on overall emissions and reinforce the importance of finding high-emitting sites quickly for effective emissions mitigation (see SI section S.7).

Time series analysis of surveys demonstrate high degree of repair effectiveness– repaired leaks do not emit in subsequent surveys.

Figure 4 shows the impact of repair activities on leaks across different components using data from the leak tags attached by the field crew. Tags are not placed on all leaking components because of access or safety restrictions. For tagged leaks that have been repaired, the operator typically includes a 'date of repair' on the tag, which helps the field crew to confirm repair activities during the subsequent survey. In our analysis, we assume that repair activities are the only reason a tagged leak would stop emitting. If left unrepaired, the tagged leak would not stop emitting automatically. There are four scenarios of the state of the leaking component as observed during subsequent surveys. First, the tagged leak was repaired and not emitting during subsequent survey with a 'date of repair' tag. Second, even though the tagged leak did not have a 'date of repair' tag, it was not emitting during the follow up survey. We assume that the operators forgot to note the date on the tag after repairing the leak and consider the leak as repaired. Third, it is possible that a tagged leak was emitting during the subsequent survey despite having a 'date of repair' tag. In this case, we assume that the leak recurred. Fourth, for tagged leaks that were emitting at the follow up survey without 'date of repair' tags, there are two possibilities: (a) the leak was not repaired and (b) the leak was repaired and recurred. Without the 'date of repair' on the tags, we were unable to distinguish between the scenarios (a) and (b).

Here, we consider emitters tagged across all five surveys and compare emissions between the survey when the tag was first created ('initial survey') and the survey when the tagged component was re-examined ('follow-up survey'). For example, at tri-annual sites, if a leak was first tagged in the November 2018 survey, the November 2018 survey is considered the "initial" survey and the subsequent May 2019 survey is considered the "follow up" survey. On the other hand, if the emission was first tagged in the August 2018 survey ('initial' survey), the subsequent survey is the

November 2018, and is considered the 'follow-up survey'. Only components with more than 20 tagged emissions are included in the analysis to ensure representativeness.

We find that emissions are persistent – leaks that are not repaired were likely to be emitting in the follow-up survey while repaired leaks remained non-emitting. The average leak rate of non-repaired flange/connecter (n = 137) stays the same between initial and follow up surveys at 4 kg CH_4/d. Similarly, valves (n = 103) that are not repaired after the initial survey exhibit similar leak rates in the follow-up survey. The increase in pneumatics (n=60) is driven by one large emitter that contribute 87% of total emissions increase at follow up surveys – without it, the average emission at follow-up surveys decreases to 7 kg CH_4/d. Thus, leaks that are not repaired do not increase significantly in size during the time between LDAR surveys.

Repairs are highly effective – leaks that are repaired stay fixed and did not recur. Flange/connector (n = 53), pneumatics (n = 57) and valves (n = 43) are all emitting, on average, <0.5 kg CH_4/d after repair. These results are significant in that the confidence intervals of leak rates for repaired emissions in the initial survey and follow-up survey do not overlap, indicating high repair effectiveness (see SI Table S10). As a result, we conclude that any increase in measured emissions in LDAR surveys is likely to come from new leaks rather than an increase in emissions from unrepaired leaks.

LDAR surveys are effective at reducing leak emissions: the average number of leaks at treatment sites are significantly lower than those at control sites, while the average number of vents do not change.

The impact of repairing leaks is further analyzed at the site level between treatment and control sites. In Figure 5, the change in site-level average number of leaks and vents are compared based on repair activities associated with different survey frequencies. A repaired site is defined by examining emissions and operators' notes associated with the tags attached to leaking components by the survey crew. Tagged leaks that stopped emitting at follow-up surveys are considered repaired regardless of whether the tag was noted with 'date of repair'. If at least one tagged leak at a site is considered as "repaired", the site is considered to have undergone repairs assuming that the operator has visited the site with the intention to fix existing emissions, even if not all tagged emissions are labeled with "date of repair". Because we could not distinguish between a not repaired tagged leak from a repaired but recurred tagged leak if the leak was emitting during the follow-up survey without a 'date of repair' (both are considered "not repaired"), the resulting sample size of "repaired" sites might be subset of all repaired sites.

Sites in the bi-annual and tri-annual treatment group underwent additional inspections besides the initial and final surveys. Accordingly, we define another category as "Repaired Consistently" – sites that underwent repairs consistently after each intermediate survey. Sites that are repaired at least once but not consistently irrespective of the survey frequency at that site, are grouped under "Repaired At Least Once". Sites that do not have any "repaired" tags throughout surveys are grouped under "Not Repaired". Based on these definitions, there are 54 sites that underwent repairs at least once, including 26 sites that are consistently repaired based on the survey frequency. Of the 26 consistently repaired sites, 15 are from the annual survey treatment group, 6 from the bi-annual survey treatment group, and 5 from the tri-annual survey treatment group. As the frequency of survey increases, the sample size of consistently repaired sites decreases. The difference between control sites and treatment sites that are not repaired is that the field crew would notify the operators of treatment sites about the emissions found on site in addition to placing physical tags on leaking components. However, operators at controls site are not notified of the results of the survey and no tags are placed on leaking components. Despite this, operators are free to conduct voluntary inspection and maintenance activities that will result in emissions reductions that are not associated with the LDAR survey.

Because the composition of site types in control and treatment groups are different, the initial numbers of average emitters in each group in Figure 5 are different (see SI section S.8). Repaired treatment sites exhibit significant reductions in the average number of leaks per site compared to control sites and non-repaired sites. Furthermore, sites that were repaired consistently saw a high reduction in the average number of leaks compared to sites that were repaired at least once. This suggest that (a) repairs are effective, (b) any observed increase in emissions likely come from new leaks and not emissions growth from existing leaks, and (c) consistent repairs of new leaks results in higher emissions reductions than inconsistent repairs. At consistently repaired treatment sites, the average number of leaks decrease by approximately 50%, from 5.0 (95% CI [3.6 – 8.0]) per site to 2.6 (95% CI [1.8 – 4.5]) per site. At treatment sites that are repaired at least once, the average number of leaks decrease from 4.6 (95% CI [3.2 – 8.2]) per site to 3.8 (95% CI [2.3 – 9.7]) per site. However, at treatment sites that are not repaired, the number of leaks increased from 1.2 (95% CI [0.8 – 1.8]) per site to 1.6 (95% CI [0.2 – 2.1]) per site, indicating the impact of new leaks created between the initial and follow-up surveys. Similarly, the average number of leaks changed from 2.3 (95% CI [1.3 – 3.8]) per site to 2.0 (95% CI [1.3 – 2.9]) per site at control sites, with the small reduction potentially associated with voluntary inspection and maintenance actions taken by the operator.

The reduction in vents between 2018 and 2019 present a more interesting challenge. Similar to leaks, the average number of vents only decreased slightly by approximately 0.3 vents per site in the control sites and 0.4 at treatment sites that were not repaired. However, by contrast, the number of vents at treatment sites that underwent leak repairs did not decrease as significantly as the number of leaks because leak emissions can be repaired by operator while vent emissions is part of operational process by design. The average number of vents reduced only slightly – from 3.5 (95% CI [2.8 – 4.2]) per site to 3.1 (95% CI [2.5 – 4.0]) per site at sites that are repaired at least once and from 4.3 (95% CI [3.2 – 5.4]) per site to 3.4 (95% CI [2.5 – 4.9]) per site at sites that are repaired consistently. The slight reduction in the average number of vents can be attributed to several potential causes. Even though vent emissions are not the target of LDAR surveys, frequent site visits give operators more opportunity to examine emissions on site and capture anomalous venting events. Additionally, large vent emissions could be episodic and thus, not detected in every survey. These reasons could possibly explain the observed reduction in vent emissions, even as the number of observed vents did not decrease significantly. That the average number of vents did not decrease substantially across all sites, whether repaired or not, suggest potential influence of significant temporal variations on overall emissions estimates.

Total emissions at control sites reduced by 36%. Even though the count of leak emissions at control sites only reduces marginally, from 2.3 (95% CI [1.3 – 3.8]) per site to 2.0 (95% CI [1.3 – 2.9]) per site, leak emissions reduced by 57%. This is understandable because operators at control sites were not made aware of the results of the LDAR survey. Because the size distribution is highly skewed, even occasional repairs of large leaks as part of routine maintenance activities (as indicated by the small reduction in the average number of leaks) can result in significant emissions reductions. For example, emissions from leaks >100 kg CH_4/d (n = 5 in 2018 and n = 1 in 2019) reduced by 81% and contribute to 94% of total leak reductions at control sites. The SI discusses the impact of LDAR surveys on total emissions (see SI section S.8).

We presented results from a large-scale, component-level, controlled experiment of the effectiveness of LDAR programs in mitigating methane emissions at oil and gas facilities. Several novel features set this study apart from prior studies in the peer-reviewed literature: (1) survey crews were deputized by the regulator and did not require operator outreach, which resulted in a fully randomized study and avoided the ‘coalition of the willing’ challenge; (2) all methane emissions, including vents, were quantified at the component-level; (3) control and treatment sites allowed analysis of LDAR program effectiveness; and (4) concurrent measurement of a large sample of gas and oil-producing sites at component-level enabled identification of site-level factors that affect emissions.

Some of the results in this study confirm prior work on methane emissions in the US and Canada. For example, we observe highly skewed emissions-size distribution – the highest emitting 5% of components contribute to 56% of total emissions and the highest 5% of emitting sites contribute to 35% of total emissions in 2019. Specifically, the 12 leaks that are larger than 100 kg CH_4/d are responsible for 10% of total emissions, underscoring the need for quickly finding these large emitters. Given their high emission rates and low incidence, leak detection technologies could trade off sensitivity for speed to achieve more cost-effective mitigation.

Tanks are the single largest source of emissions. Of all emitting components found on site, tank-related components contribute to 58% of total emissions despite only accounting for 16% of total emitters. That tanks emit significant volumes of methane has been observed in prior aerial-based surveys [27], [31]. Recognizing this, Colorado's department of public health and environment instituted an LDAR program specifically for tanks [34]. Such targeted policies to address known high-emitting sources could be a cost-effective way to reduce methane emissions.

Insights from this study can be used to develop targeted and cost-effective methane mitigation policies. For example, the distinction between leaks and vents often varies by jurisdiction and tends to increase uncertainty in the effectiveness of LDAR programs. As a result, categorizing emissions by leaks and vents may not be an effective distinction for emissions mitigation. Jurisdictions may want to consider the use of other metrics in developing mitigation policies, including a focus on the highest emitting equipment such as tanks. Additionally, our observations show significant variation in emissions across site types. Oil sites, due to the higher prevalence of tanks, emit more than twice that of gas sites on a per site basis. Similarly, multi-well batteries, both oil and gas, emit more than twice that of single well batteries. A differentiated policy that focuses LDAR surveys on facilities most prone to exhibit higher emissions is likely to be more cost-effective than one that targets all facilities with similar LDAR stringency. Our findings align with other studies in the field on the importance of locating high-emitting sites – not only because of their substantial contribution to total emissions, but also because emissions reductions are driven by these large emitters. Emissions from these sites present significant mitigation opportunities and are reasonably feasible to abate given that reduction comes from routine repairing activities [17].

A key result from this study is the empirical evaluation of the effectiveness of LDAR programs. Using detailed information from physical tags attached to leaking equipment, we find there is high persistence in leaks – leaks that are repaired remain fixed in follow up surveys, while leaks that are not repaired remain emitting without significant increases in their emission rate. This implies that, (1) repairs are highly effective, and (2) any increase in measured emissions in LDAR surveys is likely to come from new leaks rather than an increase in emissions from unrepaired leaks. Given the skewed emissions distribution, the success of LDAR programs, therefore, rely on quickly finding high emitting, new leaks.

In addition to emissions, our study also consistently tracked the number of leaks and vents before and after every periodic LDAR survey – a dataset that was not available from prior research. At treatment sites that underwent repairs, LDAR surveys significantly reduce the average number of leaks per site from 5.0 (95% CI [3.6 – 8.0]) to 2.6 (95% CI [1.8 – 4.5]). By contrast, control sites only exhibit a slight reduction in leaks from 2.3 (95% CI [1.3 – 3.8]) to 2.0 (95% CI [1.3 – 2.9]) per site, likely from voluntary inspection and maintenance activities. Similarly, treatment sites that are not repaired see the average number of leaks increase slightly from 1.2 (95% CI [0.8 – 1.8]) to 1.6 (95% CI [0.2 – 2.1]) leaks per site. This evidence, even without considering corresponding emissions reduction, clearly show the effectiveness of LDAR surveys and the importance of the repair process in addressing leaks.

Materials and Methods

Site Selection: Sites were selected from publicly available data on operating oil and gas upstream facilities from Canada's Petroleum Information Network (Petrinex) [35]. Because the study is designed to be randomized and anonymized, no operator was consulted during the site selection process. Site access was guaranteed by the Alberta Energy Regulator (AER) that deputized the field crew to conduct LDAR surveys. Deputization provided the field crew with the same freedom of access provided to the AER under provincial legislation. This further allowed the study to avoid the 'coalition of the willing' challenge often observed in component-level methane emissions studies where operator consent is often required for site access and ground-based surveys. However, the field crew did not encounter any opposition from operators and did not have to use the AER deputization to access sites for measurements. Some selected sites were not surveyed due to various operational and environmental conditions, such as road conditions or ongoing maintenance work.

We selected 204 sites across a 50 km x 50 km region within the Red Deer production area. The Red Deer region is in Central Alberta and is characterized by natural gas and light oil production. The representativeness of the distribution of site types in the study sample to the Red Deer production region was verified using 2-sample Kolmogorov–Smirnov test (see SI section S.1.1). Five major site types were included in the study sample – gas single well battery (Gas SW), gas multiwell group battery (Gas MW), crude oil single-well battery (Oil SW), crude oil multiwell group battery (Oil MW), and crude oil multiwell proration battery (Oil MWPro) (see SI section S.1.2) [36]. The number of sites selected for each site type is representative of the distribution in the Red Deer region. Next, selected sites were divided into four groups based on the number of LDAR surveys that would be conducted over the course of one year: (1) control sites where operators will not be informed about emission sources, and treatment sites that are visited (2) annually, (3) biannually, or (4) tri-annually where operators will be informed about emission sources and asked to undertake repair activities. The initial benchmark survey for all control and treatment sites was conducted from August to October 2018. The final survey was conducted in fall 2019 from August to October on all control and treatment sites. Annual sites and control sites were only visited in the initial and final surveys. Bi-annual sites underwent intermediate LDAR survey in March 2019. Tri-annual sites underwent intermediate surveys in November 2018 and May 2019. Sites that were not able to be consistently visited on schedule -- either because of a change in status of a site (for example, shut-in during the study period) or weather conditions -- were removed from our analysis (see SI section S.1.2 for detailed breakdown).

Field Survey Methodology: Davis Safety Consulting Ltd. (henceforth 'field crew') were contracted to conduct all ground based LDAR surveys in this study because of their prior experience in collecting research-quality data [29]. The field crew were trained in the use of FLIR GF-320 OGI camera and the Providence Photonics' QL320 quantitative OGI tablet (QOGI) for methane emissions detection and quantification, respectively [37], [38]. The GF-320 is the industry standard in LDAR surveys across North America [34], [39]. QOGI was selected over the conventional Bacharach Hi-Flow sampler because: 1) QOGI is able to quantify all emissions whereas Hi-Flow Sampler can only estimate emissions that are accessible and safe; 2) QOGI has a wider range of measurement capabilities while Hi-Flow Sampler is limited by the maximum displacement of the blower; and 3) QOGI avoids recent challenges associated with Hi-Flow Sampler around gas composition, sensor transition failure, and calibration that could underestimate emissions [40]–[43]. Despite our efforts and precautions to generate reasonable emission quantifications, the accuracy of QOGI and other image-based detection technologies fundamentally relies on plume detection algorithms that distinguish plume pixels from non-plume pixels on the OGI camera. A recent controlled release study found that the QOGI technology has a high accuracy when interpreted in an aggregated context, with a bootstrapped error of +26%/-

23% from a sample size of 50 emissions, similar to those observed from Bacharach Hi-Flow samplers [44]. However, individual quantification estimates can have higher uncertainties.
The site visit process is as follows: one member of the field crew examines each component and equipment with the infrared camera for emissions, both leaks and vents. A second member of the crew records meta data on every emission and attaches a physical tag to a leak, if necessary. Tags are noted with unique identification numbers and are only used for leak emissions that are safe to access at treatment sites. No tags are used at control sites to allow comparison of performance against treatment sites where repairs are conducted. In contrast, at treatment sites that were visited at annual, bi-annual, and tri-annual survey frequency, the field crew notified the operators of the emissions found on sites for subsequent repair after each survey, with the understanding that the field crew may return to conduct a post-repair LDAR survey. Although operators of control sites were not informed of the emissions found by the field crew (with exceptions for safety), they were also not explicitly asked to not conduct repairs, so emissions change at control sites over the course of the year can be considered a proxy for voluntary inspection and maintenance activities.

In contrast to regulatory LDAR surveys, the field crews were instructed to detect and measure all methane emissions at sites, including permitted vent emissions that will not undergo repair process. This was done for two reasons. One, measuring all emissions provided critical insights into the relative importance of leaks and vents in methane mitigation that is often not available in the literature. Two, it provided a more nuanced understanding of the source of large emissions observed at oil and gas facilities.

Data Collection: When an emission was detected, the field crew would find an appropriate angle to take several videos using a tripod mounted FLIR GF320 to visualize and quantify the emission. The field crew would also measure the imaging distance with a range finder and determine the windspeed and temperature using an anemometer. In addition, the field crew would record an image and a 15~30 second video of every emission found on site to assist operators with the repair process and generate a record for every detected emission.

In addition to quantitative data on methane emissions, the field crew also collected other ancillary data on site to assist with analysis and interpretation. At the site level, the field crew collected data on operator name, site name, legal subdivisions (LSDs), production type, and major equipment count. At the component level, the field crew recorded a detailed description of the emission including its location, emitting component, equipment, and whether the emission was a leak (unintentional emissions, also referred to as “fugitive emissions”) or a vent (intentional emissions). While definitions vary across jurisdictions, emissions were categorized as leaks if they were a result of component malfunction or emissions from equipment with control devices. Vents, on the other hand, included pneumatic devices in normal operation, open-ended lines, abnormal emissions from vent sources (e.g., open thief hatch from an uncontrolled tank battery), and other equipment that emit methane by design.

Data Analysis: All emissions were mapped into six major component categories [39], [45]: flange/connector, open-ended line (disaggregated into tank and non-tank), pneumatics, tank level indicator, thief hatch, and valves. There are two scenarios in which emissions could not be quantified using the QOGI system. In the first scenario, the emission size was too small for the QOGI system to quantify. Here, we assigned an emissions rate corresponding to the lowest measured emission rate for that component type in that survey. 0.6% of the emitters were assigned an emission rate using this method. In the second scenario, the emission was not quantifiable due to unfavorable atmospheric conditions or interference from nearby emissions. Here, we assigned an emission rate corresponding to the average emission rate from the emitting component-type in that survey. 4% of the emitters were assigned emission rates using this method (see SI section S.1.4). All emissions are reported in mass flow rates, with an average volume weighted methane content in natural gas of 0.82 representative of the Red Deer region (see SI section S.1.3) [11].

To derive proportional loss rates (PLR), we retrieved monthly production data for each site from Petrinex [35] and correlated these with the corresponding QOGI survey months. Because the Red Deer region includes production of both oil and gas, we used an energy-based allocation method to calculate PLR_e as shown in Equation (1) [29]. The SI discusses PLR based on natural gas throughput (see SI section S.5).

$$PLR_e(\%) = \frac{Energy\ from\ Methane\ Emission\ \left(\frac{GJ}{mo}\right)}{Energy\ from\ Gas\ Production\ \left(\frac{GJ}{mo}\right) + Energy\ from\ Oil\ Production\ \left(\frac{GJ}{mo}\right)} \quad (1)$$

Future recommendations and limitations to the data analysis in this study are presented in SI Section 9.

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