Extrapolation Approaches for Creating Comprehensive Operator-level Measurement-Based Methane Emissions Inventories

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SYNOPSIS: We outline statistically valid, practical methods for operators to develop natural gas production segment methane emissions inventories using measurements originally obtained for leak detection purposes.

ABSTRACT

Measurement-based methane emissions inventories are essential for U.S. oil and natural gas operators to track their progress toward emissions targets and to demonstrate the impact of improved operational and monitoring practices. However, translating raw emission measurement data, whether from continuous monitoring systems, aerial flyovers, or operational cause analyses, into emissions inventories is nontrivial, and advertised inventory numbers are often void of any information about the methodology used to produce them. In this paper, we introduce the concept of a comprehensive measurement-based emissions inventory, which represents all emissions across the entire time frame, across all spatial assets, and of all emission sizes for the target scope. We carefully characterize some of the extrapolation efforts necessary to create a comprehensive emissions inventory estimate with data from either continuous monitoring systems or aerial flyover measurements. Understanding these methods is essential for operators and researchers desiring defensible emissions inventory reports that adhere to reporting frameworks such as Veritas and the Oil and Gas Methane Partnership 2.0. We provide simple examples to illustrate the sensitivity of annual emissions estimates to the various extrapolation approaches and highlight the challenges, strengths, and limitations when working with data from each of the technologies.

1. Introduction

Methane emissions from across the oil and natural gas supply chain are an important policy and climate topic, globally. Methane (CH_4), the primary component of natural gas, is a short-lived climate pollutant that has an 82.5 ± 25.8 times greater climate impact than carbon dioxide on a 20-year timeframe and 29.8 ± 11 on a 100-year timeframe.[1,2] Given the near-term impact of every kg of CH_4 emitted, natural gas companies have an impetus to identify the largest sources of emissions and to initiate mitigation strategies targeting these sources. The methane intensity (emissions per production) of natural gas has also grown into a marketable quantity, as there is interest in gas associated with lower overall emissions if it can be confidently determined.[3–5] The U.S. Environmental Protection Agency's (EPA) Greenhouse Gas Reporting Program (GHGRP) Subpart W is the current regulatory standard for reporting methane emissions from petroleum and natural gas activities in the United States for covered facilities.[6]

Emission inventories are valuable tools that can be used to track and compare emissions,[7–9] identify opportunities to limit pollution,[10,11] minimize wasted energy, and even save money.[12–14] Inventories have traditionally been developed using Bottom-Up (BU) methods that combine broad, generic emission factors with activity factors that estimate the frequency of emission events and equipment/component/site counts (e.g., heaters, separators, blowdowns) to get a total emissions estimate. The GHGRP regulations include the development of annual BU inventories at the facility level, and the EPA Greenhouse Gas Inventory (GHGI) extends these data to estimate regional and national totals. Emission inventories reported in the literature often focus on measurement-based, or Top-Down (TD), approaches for large geographic areas such as a basin, state, or nation.[15–19] TD studies have often shown emissions that are higher than estimated by the GHGI.[7,18–20] However, other researchers have developed BU inventories that agree with these TD estimates and suggest the GHGI underestimate stems from underestimating the impact of intermittent high-emission events.[7,9,21,22] Generally, persistent emissions can be linked to leaks and design emissions, such as pneumatic controllers and compression systems,[23] whereas intermittent sources can include abnormal operating conditions like inefficient or unlit flares[23–26] and operational emissions such as blowdowns and manual liquid unloadings.[23,27] While operators have begun documenting some known emissions events, such as blowdowns, capturing accurate emissions data on unexpected abnormal conditions remains a significant challenge.

TD methods rely on emissions measurement data collected over different spatial and temporal scales from technologies with varying performance characteristics (e.g., probability of detection (POD), site- vs component-level attribution).[28–31] For example, snapshot aerial surveys can measure every active site during a campaign to provide full spatial coverage; however, they only briefly measure each site. Conversely, point sensor networks (PSN), sometimes referred to as continuous monitoring systems, detect and quantify site emissions continuously under acceptable environmental conditions, yet they are frequently not deployed at all sites due to their cost. Extrapolating the measurements from this monitored subset of sites to estimate emissions from unmonitored sites can introduce significant uncertainty to the resulting inventory.[19,32] Furthermore, both aerial surveys and PSNs are limited in their ability to detect small leaks based on their POD, which depends on the methane quantification technology used, data collection characteristics (e.g., flying altitude, number of sensors), and wind conditions.

As a result of these considerations, a third type of emission inventory called a measurement-informed inventory (MII) that integrates BU and TD data, leveraging the relative strengths of each approach, has been the focus of recent literature.[10,15,33] Theoretically, such MIIs provide pathways to obtaining a more accurate estimate of emissions and are the focus of several proposed monitoring frameworks, such as Veritas,[34] higher levels of the MiQ gas certification program[35] and the Oil and Gas Methane Partnership (OGMP) 2.0.[36] In this work, we discuss inventories using the following terminology. A "measurement-based emissions inventory" relies solely on measurement data and uses extrapolation procedures to obtain a total emissions estimate with the desired temporal, spatial, and emissions ranges (e.g., for a subset of facilities or time). A "comprehensive" emissions inventory is any inventory that completely reflects all temporal, spatial, and emissions ranges for the target scope (e.g., annual total emissions for all facilities for one operator).

The pathway to creating the most accurate MII involves reconciliation analyses that identify reasons for the agreement or disagreement between different inventories, either TD and BU or inventories relying on different emissions measurement information.[36–38] Such reconciliation is only possible if the inventories are estimating the same quantity, meaning they have the same spatiotemporal scope and estimate total emissions across that scope.[22,38–40] Both extrapolation and reconciliation require analytical assumptions and rely on methodological decisions that can significantly impact and bias the estimated emissions. However, there is currently no standardized method. The differences in spatial, temporal, and emissions size coverage across measurement technologies further complicate this situation.

Given the lack of standardization amid growing interest in MII development, this study aims to document and demonstrate practical pathways for creating a comprehensive measurement-based inventory. We propose multiple extrapolation methods, outline their underlying assumptions, and discuss the variability across the resulting emissions estimates. To do so, we utilize anonymized production data and emissions monitoring data from PSN and aerial surveys to develop two annual, comprehensive measurement-based inventories.

2. Materials and Methods

2.1. Extrapolation and Integration Considerations

We consider three data sources in this study: two PSN technologies (PSN A and PSN B) and one aerial survey method. These measurement technologies were originally deployed for leak detection and repair (LDAR) rather than for creating or informing emissions inventories, which introduces various critical nuances to the data that should be considered. While LDAR efforts are valuable in detecting and addressing leaks,[11,41–43] several studies have stressed the importance of representative sampling to develop appropriate MIIs,[15,32,40] and LDAR measurements may not collect a representative sample.

One LDAR aerial survey strategy is conducting an initial flight over all sites to detect emissions, followed by a second flight over only the sites with detected emissions to assess whether those emissions persist.[15,44,45] Developing a probabilistic model to account for the second flight's sampling bias is non-trivial and yet necessary to incorporate said data into an inventory estimate. For the purposes of this study, we focus solely on the first flight of each aerial campaign, as they represent spatially complete snapshot surveys of all facilities.

PSNs are thought to have excellent temporal resolution, while their spatial resolution is dependent on their level of deployment across sites. Spatial extrapolation is needed to estimate emissions for the sites without a PSN to create an emissions inventory. Temporal extrapolation is also necessary to infer emissions before the PSN installation and for periods when the environmental conditions were outside the operational envelope of the PSN.

Lastly, all technologies have detection limits. To develop a comprehensive inventory the dataset must be augmented with estimates of undetected emissions. Auxiliary information or assumptions about the emission size distribution, often referred to as the expected emissions distribution, are required to do so. This augmentation may not be necessary if it can be demonstrated using an expected emissions distribution that undetected emissions represent a minor contribution.

As shown in Figure 1, there are several steps to using emissions measurement data to create an MII. The first step is to perform extrapolation of the monitoring data to develop a comprehensive measurement-based inventory. For each technology and dimension (i.e., spatial, temporal, emission size distribution), we detail several methods that vary in complexity. In this work, we consider extrapolation methods that apply to a single dimension and then layer methods to obtain a procedure that accounts for all necessary extrapolations. We begin by inferring undetected emissions during monitoring times in Section 2.3. Next, we apply temporal extrapolation to get annual estimates for monitored sites in Section 2.4. Finally, we apply spatial extrapolation to infer emissions from unmonitored facilities in Section 2.5. Simple extrapolation approaches can be useful when the assumptions are reasonable; however, often, more advanced extrapolation methods will result in more accurate extrapolations, given systematic biases in the spatial and temporal deployment of the technology. Nevertheless, any error in emission event frequency estimation or emission quantification will translate through the extrapolation to error in the final inventory. Thus, the emission rate quantification technology used fundamentally affects the quality and uncertainty in any developed inventory.

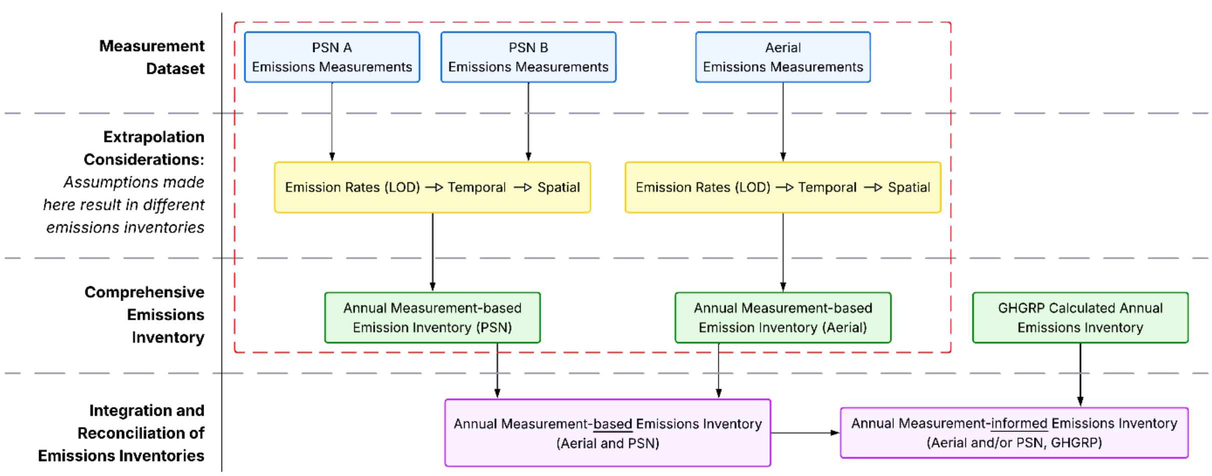

Figure 1. Flow diagram detailing all steps required to develop a measurement-informed emissions inventory. The focus of this work is highlighted in the red box.

The second step is integrating two or more of the developed emission inventories. This is where reconciliation occurs to produce an MII believed to provide the best representation of actual emissions. This can be as complex as the extrapolation.

2.2. Anonymized Dataset

This work uses anonymized production and emissions measurement data collected in 2023 from a dry-gas basin for a subset of sites shared by our operator partners. The anonymization is detailed in Supporting Information (SI) Text S1 and is intended to preserve important features and relationships in the data while making true values unrecoverable by a third party given the confidential nature of the data. A total of 200 anonymous sites were selected with all sites having been surveyed in two aerial surveys, 50 sites having PSN A, and 50 sites having PSN B. The aerial surveys use airborne Gas Mapping LiDAR (GML) to calculate emission rates[43,46] while the PSNs use one or more calibrated metal oxide CH4 sensors or tunable diode laser sensors and anemometers installed on-site to calculate an emission rate using proprietary formulae. Both PSNs report emission rates as 15-minute averages, but PSN A reports 0 when no emissions are measured and "NA" to indicate unable to calculate an emission rate while PSN B excludes both such times. To make the PSN data sets more congruent and simplify the analysis of the PSN data, we randomly replaced PSN B missing intervals with zero and NA, such that the ratio of zeroes relative to NA matches that of PSN A (33%). This simplification treats the PSNs as though they have comparable performance, which we note is not necessarily the case under real world conditions.[47] Figure 2 summarizes the relative coverage of each dataset along the various dimensions.

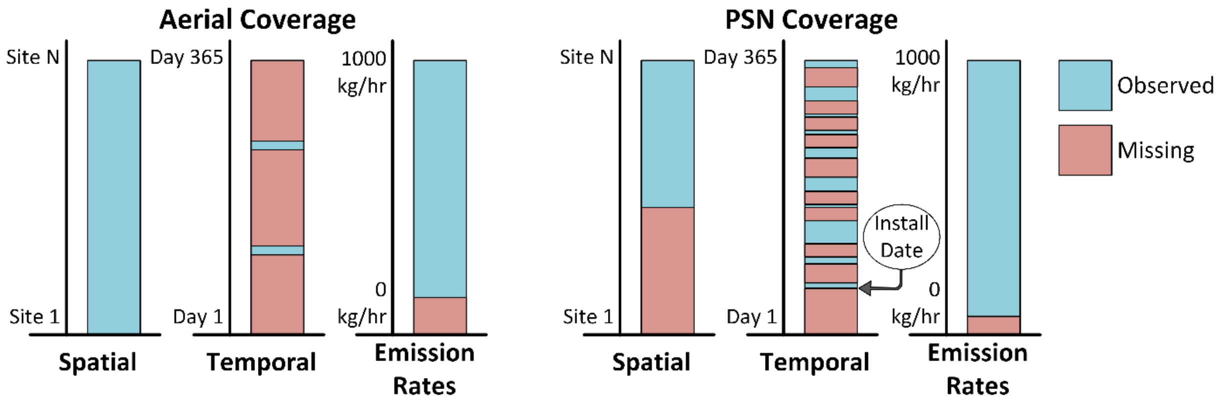

Figure 2. Qualitative diagrams showing the relative coverage of the aerial survey and the PSN data across each dimension. The aerial survey data consists of two campaigns covering all sites (Spring and Fall, 2023). Deployment of PSN on sites occurred throughout the year, creating an additional unmonitored period for many sites at the beginning of the year.

2.3. Emission Rate Coverage

2.3.1. Aerial

Aerial surveys can scan many facilities relatively quickly, but their ability to detect emissions depends on several factors, including sensor type, survey height, wind speed, and emission size. Typically, there is a trade-off between spatial coverage and detection sensitivity, where flights conducted at higher altitudes can scan facilities more quickly but at the expense of missing small emissions. Several studies have examined the POD for human-piloted aircraft surveys.[28,46,48,49] The aerial surveys in this work were conducted at relatively low altitudes to enable the attribution of emissions to specific sources for the purposes of LDAR. This particular vendor has developed methods to determine the POD using the emission rate and survey-specific information with a typical 90% POD of 1.27 kg/h[46], however we are using the described production sector >90% POD of 3 kg/h in this work.[43,50]

2.3.2. PSN

The two PSN technologies used in this work report slightly different detection capabilities. Vendor listed performance specifications detail that PSN A can detect emission rates as low as 0.4 kg/h at distances up to 100 m, though this may represent a minimum detection threshold (POD > 0%) rather than an established 90% POD based on controlled release testing. PSN B has undergone testing at the Methane Emissions Technology Evaluation Center (METEC) that determined a minimum detection threshold of 0.12 kg/h and a 90% POD of 1.5 kg/h.[51]

2.3.3 Extrapolation Methods

For aerial survey data we consider a simple method to account for undetected emissions based on the stated POD (see Table 1). For simplicity, our approach treats the >90% POD as a LOD threshold assuming all emissions above are measured. We leverage the emission rate distribution of Omara et al., [52] subset to only dry gas basins, to estimate the average emission rate and fraction of emission rates below this LOD. Briefly, Omara et al.[52] combined site-level production sector emissions data from previous studies with Enverus™ (Austin, TX USA) activity data using a statistical resampling method to develop a national emission rate distribution. Note that other national emission rate distribution estimates exist and could alternatively be used as the reference distribution.[8,9] For comparison, we also consider the assumption that there are no emissions that are undetected given the high sensitivity of the instruments used in this work.

In the Omara et al.[52] distribution, 24% of sites have emissions above a LOD of 3 kg/hr and 57% have non-zero emissions below this LOD. We estimate the fraction of sites with undetected emissions by assuming the 57% to 24% ratio is the same for our population of sites, and then account for any observed measurements below the LOD. Mathematically, this estimate for the proportion of undetected emissions can be expressed

$$(0 < x < \mathrm{LOD})_{undetected} = \left(\frac{0<x<\mathrm{LOD}}{>\mathrm{LOD}}\right)_{\mathrm{Omara}} \times (> \mathrm{LOD})_{\mathrm{measured}} - (< \mathrm{LOD})_{\mathrm{measured}} \quad \text{Eq. 1}$$

We convert the percent of measurements calculated in Equation 1 to a number of measurements and assign this number of non-emitting sites the average non-zero emission rate between 0 and 3 kg/h from Omara et al.[52], which is 0.922 kg/h.

Applying this approach using the PSN LOD and data resulted in negative corrections due to the low LODs and many measured emission rates below the LOD. Therefore, no adjustments were made to the PSN emission records to adjust for undetected emissions. If a different reference distribution[8,9] were used, it is possible some correction may be warranted.

Table 1. Extrapolation approaches for inferring emissions below the LOD.

Extrapolation Method	Description	Assumptions	Advantages/Disadvantages
1. Assume all emissions are measured	Use data without modification	All emission rates are detectable by the technology	+ Easy to implement - Underestimates total emissions, particularly with less sensitive technology
2. Augment observed emissions events with an additional undetected set of events based on fraction of literature expected emissions distribution below technology LOD	Use literature emission rate distribution to estimate number of emissions events undetected	Literature emission rate distribution accurately reflects true distribution of emissions on surveyed sites	+ Relatively easy to implement + Directly accounts for small, missed emissions using best available data - Simplistic approach that does not fully account for low emissions

2.4. Temporal Extrapolation

2.4.1. Aerial

The aerial survey data are instantaneous snapshot measurements of the emissions from facilities. These observed emission rates must be extrapolated to all other times when the sites are unobserved. Since not all sites operate continuously throughout the year, three different extrapolation approaches were used.

In the first approach, aerial temporal method one (AT1), each observation is extrapolated across the year based on the number of observations at that site (i.e., two aerial emission observations would each be extrapolated over six months). While this extrapolation in essence assumes all sites with non-zero emissions emit constantly year-round, it is mathematically equivalent to computing the mean emission rate across all sites and assuming that is the true mean emission rate across all sites over the entire year. This extrapolation approach aligns with the ergodic hypothesis, which states that an average over the emissions measurements at many sites is equal to the time-averaged emissions at a single site, assuming sites are relatively homogeneous.[53]

In AT2, extrapolation accounts for site-specific production months, ensuring that emissions are only projected for the months that a site was actively producing. This method results in equal or lower estimated emissions compared to the first approach, though it may underestimate emissions since wells that are not active can still emit.[54–57] Note that no duration information is required here as we assume that the relative frequency of the observed emissions reflects the frequency and duration of the emission events.

In AT3, aggregated production-normalized emission rates are used in extrapolation rather than scaling emissions at the individual site level. Specifically, total emissions observed during each flyover are summed across sites, converted to monthly emission rates assuming 730 hours per month, and divided by the total production from all sites during the corresponding month to get an average emission intensity (i.e., emissions per unit of gas produced) for the month flown. The intensities are then multiplied by the total production for each half of the year and summed. This method assumes that emissions are proportionally related to production at the fleet level as suggested by previous research,[52,58–60] though the relationship was weak, and accounts for temporal fluctuations in production over time offering a broader, system-level estimate of total emissions.

2.4.2. PSN

For many sites equipped with PSN, emission rate records are missing for large portions of the year. There are two primary causes of the missing values: (1) unmonitored periods, often before the PSN is installed on the site, and (2) periods of no information, when the PSN is actively monitoring the site, but the environmental conditions prohibit emission rate estimation. Note that the term "period of no information" used here is adopted from Daniels et al.[61] The portion of the year designated as periods of no information varies significantly across PSN A sites (see SI Figure S1), with an average of 61% of recorded time intervals (i.e., excluding unmonitored periods) classified as periods of no information (range: 35% to 94%). In some cases, this includes large windows (e.g., weeks to months) that are periods of no information. For context, Chen et al.,[62] estimated via simulation that 78% of time would be periods of no-information with one sensor and 45% with four sensors for a single source emission event.

Table **2** outlines several approaches for temporally interpolating through periods of no information, labeling these as PSN temporal methods (PT).

Table 2. Approaches for temporal extrapolation for missing emission rates from PSNs due to periods of no information, listed in order of simplest to most complex.

Extrapolation Method	Description	Assumptions	Advantages/Disadvantages
*PT1. Assume all missing emission rates are 0	Set all missing emission rates during periods of no information to zero	No emissions occurred during time intervals when data is missing	+ Easy to implement - Likely underestimates emissions

Extrapolation Method	Description	Assumptions	Advantages/Disadvantages
PT2. Naïve scaling of total observed emissions by fraction of time emission rates were estimable (i.e., periods of information)	Calculate PSN total across all sites and multiply by a missing scaling factor (total interval count / intervals with emission rates reported). Equivalent to setting all periods of no information to the average measured emission rate across all sites with PSNs.	Data recorded is a representative sample of emissions across all PSN sites throughout the year	+ Easy to implement + Wind is likely exogenous to cause of emissions so assumption of representativeness of sample is likely to hold - Does not leverage temporally nearby emission rate information on either side of the missing window on a given site
PT3. Naïve scaling of site-level observed emissions by fraction of time the site emission rates were estimable (i.e., periods of information for the site)	Equivalent to method 2, but applied at the site level, rather than in aggregate.	Data recorded for the site is a representative sample of emissions for that site throughout the year	+ Relatively easy to implement + Acknowledges possible site-to-site variability in total emissions - Sites with very few reported emissions will have more variable scaling
PT4. Linear interpolation between emission rates on either side of missing window	Connect the emission rates during time windows just prior and just after period of no information. If the first or last time point is missing, extrapolate single observed rate through entire window. See SI Text S2 for more discussion.	Average emission rate in period of no information is well estimated by empirical average of observed endpoint emission rates.	+ Leverages information on site at time periods surrounding period of no information - Emission rates inferred are variable and if period of no information is large, method can extrapolate rare emission rate over large period

*The first row is shaded red to highlight that it is not considered a valid approach to temporal extrapolation but is included here for comparison purposes.

For unmonitored periods, we temporally extrapolate using a method analogous to AT2: multiply the PSN total by a scaling factor that accounts for non-producing months (total months producing

/ months monitored). This method was selected since unmonitored periods are typically months long and is applied in an aggregate or site-specific manner to match the PSN temporal method.

2.5 Spatial Extrapolation

2.5.1. Aerial

The operator shares an updated site list with the aerial survey vendor a few weeks before each flight to define the scope of the survey. Therefore, the survey provides 100% spatial coverage across active sites, and no spatial extrapolation is required. This does not imply that all emissions from every source are detected, but merely that all emission events, even those that are rare, are within the sampling frame (e.g., leak from a tank, blowdown event, flare, vent). Hence, we assume the observed emission rate distribution is representative of the true emission rate distribution.

2.5.2. PSN

Each of the approaches described here assumes that any necessary temporal extrapolation has already been performed for the PSN data, and therefore, the key remaining extrapolation step is to infer emissions at the sites without PSNs. To do this, it is critical to understand potential differences between the characteristics of monitored and unmonitored sites. If site emissions are correlated with site characteristics that exhibit notable differences between the groups of monitored and unmonitored sites (i.e., newer sites, larger producing sites), extrapolation approaches ignoring these site-level characteristics may result in biased emissions inventories.[15,19,32,40] For example, Sherwin et al.[19] showed methane emission intensities that differed by more than a factor of two across sub-basins within the Permian. This stresses the importance of appropriately considering different types of facilities through stratification. We treat PSN A and PSN B data as a single PSN dataset during spatial extrapolation. This assumes a site with PSN A is as well measured as PSN

B, which may not be true given different technology performance metrics (e.g., POD) and algorithms used to convert measured concentrations into reported emission rates.

Figure 3 summarizes site characteristics for the monitored and unmonitored sites, partitioned by technology provider with more details provided in SI Table S1. Most notably, the unmonitored sites are older and have lower annual production. Focused on LDAR, the operator prioritized installing PSNs on newer, high-production sites, as reflected in these statistics. Table 3 outlines the three PSN spatial extrapolation methods (PS) considered here. Two of these methods consider differences in facility characteristics, with PS2 stratifying facilities into inactive/no data, marginal production (1 – 15 barrels of oil equivalent per day, BOED), standard production (16 – 300 BOED), and high production (>300 BOED) facilities.

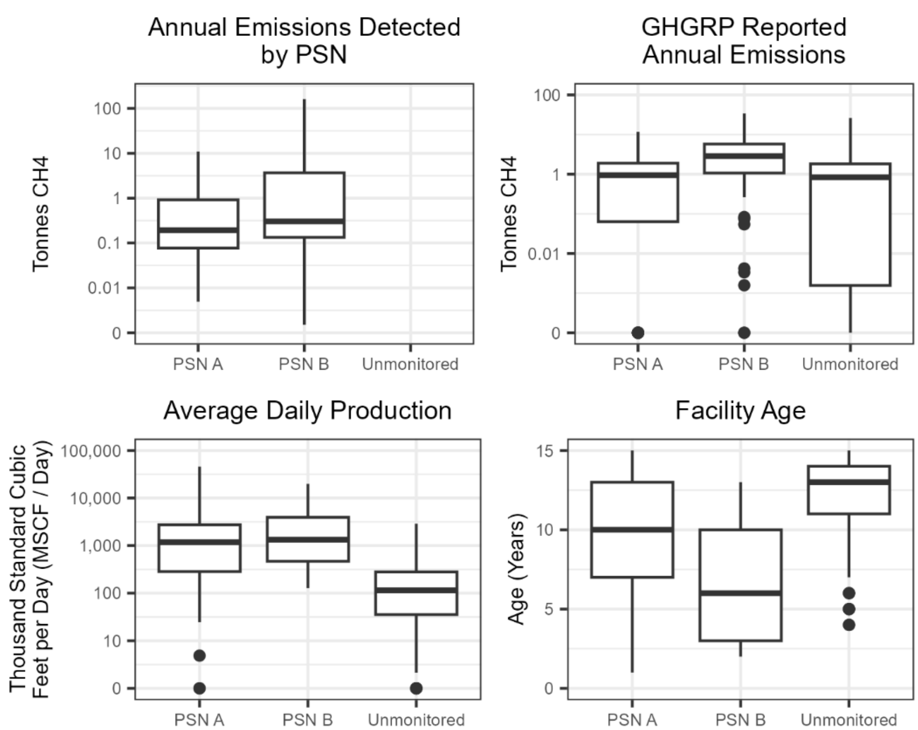

Figure 3. Distributions of site characteristics partitioned by whether it is equipped with PSN, and if so, what provider. Differences between monitored and unmonitored sites may be important to account for when creating a comprehensive measurement-based emissions inventory.

Table 3. Spatial extrapolation approaches for PSNs are listed in order of simplest to the most complex.

Extrapolation Method	Description	Assumptions	Advantages/Disadvantages
PS1. Naïve scaling by the fraction of sites monitored	Calculate the total emissions from both PSN providers and multiply value by a site scaling factor (total site count / monitored sites)	Sites with PSN are a representative sample of all sites	+ Easy to implement - Figure 3 suggests the representative assumption may not be appropriate
PS2. Scaling by fraction of sites monitored within each production strata	Compute total PSN emissions for each production strata and multiply by a strata-specific site scaling factor (total site count in strata / monitored sites in strata), and sum across all strata	Sites with PSN within each production strata are representative of all sites in the strata	+ Easy to implement + Method can be replicated at basin-level since production data is publicly available - Figure 3 suggests the representative assumption may not be appropriate
PS3. Multivariable prediction model	Estimate multivariable regression model to predict total site emissions as detected by PSN as a function of site characteristics (age, production, GHGRP reported emissions)	Relationship between site characteristics and emissions on sites with PSN is the same for sites without PSN.	+ More refined predictions of emissions at site level, which can account for biased placement of PSN on specific types of sites - Implementation requires software that performs multivariable regression

3. Results and Discussion

3.1. Applying Extrapolations to Aerial Surveys

The values in Table 4 show comprehensive measurement-based emissions inventories using the aerial data. These results account for all three comprehensive inventory dimensions, using temporal extrapolation and a <LOD correction. The LOD correction adds between 270 and 291

metric tons (MT) CH_4, depending on the method of temporal extrapolation, which equates to only ~4.5% of the total. The choice of temporal extrapolation method also has little impact on the result. Emissions including the LOD correction across temporal extrapolation methods differ by less than 5% relative to the average across all three methods (6,233 MT CH_4).

Table 4. Temporal extrapolation results for the aerial survey data for the monitored sites.

Temporal Extrapolation Method	Temporally Extrapolated Inventory (MT CH_4)
AT1 – Assuming consistent emissions for 6 months from aerial measurement	6153
- Accounting for LOD	6444
AT2 – Account for production months	5949
- Accounting for LOD	6219
AT3 – Proportional scaling of production	5764
- Accounting for LOD	6036

Our estimated contribution from undetected emissions is lower than reported by other recent works. Previous studies have reported undetected emissions or emissions with 0% < POD < 100% can represent as little as 5% to over 85% of total emissions depending on the basin.[15,19,43,45,63] Given this large range, we cannot determine whether our ~4.5% estimate is low due to the study area or methodology.

3.2. Applying PSN Temporal Extrapolations

In general, the linear interpolation and naïve scaling methods for PSN A (PT2 – PT4) all provide similar results, whereas assuming all missing emission rates are zero (PT1) provides a substantially smaller estimate (see Table 5). Table 5 first displays the extrapolation method results for periods of no information and then includes the extrapolation method for unmonitored periods layered on top. When accounting for unmonitored months, methods PT2 – PT4 differ by at most 11% relative to the average across them (141 MT CH_4) while PT1 differs by 81% relative to 141 MT CH_4.

Table 5. Temporal extrapolation results for the PSN data for the monitored sites.

Temporal Extrapolation Method for Periods of No Information	Partial Inventory (MT CH_4)	
	PSN A	PSN B
PT1. Assume all missing emission rates are 0	45	322
- Accounting for unmonitored months	60	474
PT2. Naïve scaling of total observed emissions by fraction of time emission rates were estimable	118	734
- Accounting for unmonitored months	155	1082
PT3. Naïve scaling of site-level observed emissions by fraction of time-specific site emission rates were estimable	98	513
- Accounting for unmonitored months	127	540
PT4. Linear interpolation between emission rates on either side of missing window	109	342
- Accounting for unmonitored months	141	356

The results for PSN B are notably different than those for PSN A. First, partial inventory emissions calculated using PSN B are higher on average than PSN A. This is unsurprising given the differences in the facilities being measured, as shown in Figure 3, though may also indicate differences in performance between PSN A and PSN B. The fraction of unmonitored data is also less consistent across sites for PSN B as compared to PSN A (see SI figure S2), with higher emitting sites generally being more heavily monitored. This biased monitoring is likely why the PT2-derived inventory is so much higher (~80%) than the average across PT1, PT3, and PT4 for PSN B (457 MT CH_4), unlike what we see for PSN A. Additionally, more heavily sampling higher emitters causes unmonitored periods to have a bigger impact if extrapolating aggregated data (PT1 and PT2), and a more minor impact if extrapolating site-level data (PT3 and PT4) as compared to PSN A.

3.3. Applying PSN Spatial Extrapolations

There are substantial differences between the estimated inventories depending on the spatial extrapolation approach, as shown in Table 6. Specifically, PS1 results are 1.8 times larger and PS2 results 1.2 times larger on average than those of PS3. All results presented have already been temporally extrapolated, including accounting for unmonitored periods, such that they represent annual estimates. As such, these results represent comprehensive measurement-based inventories based on the PSN data. Results exclude PT1 as it was discussed that it is not considered a valid approach, and PT2 is only included in PS1 as PT2 aggregates all sites before temporal extrapolation and PS2 – PS3 can only be applied at the site level.

Table 6. Results from PSN spatial extrapolation methods.

Spatial Extrapolation Method	Spatially Extrapolated Partial Inventory (MT CH_4)
PS1. Naïve scaling by the fraction of sites monitored	
- PT2	2474
- PT3	1335
- PT4	995
PS2. Scaling by fraction of sites monitored within each production strata	
- PT3	849
- PT4	668
PS3. Multivariable prediction model	
- PT3	740

- PT4	562

3.4 Comprehensive Emissions Inventory Estimates

Table 4 and Table **6** represent our comprehensive measurement-based inventory estimates for aerial survey and PSN data, respectively. The aerial survey results range from 6,036 MT CH_4 to 6,444 MT CH_4 while the PSN results range from 562 MT CH_4 to 2,474 MT CH_4, even though the spatio-temporal scope of each inventory is the same. We discuss this discrepancy in Section 3.5. For both measurement systems, the method choice for temporal extrapolation had a minimal impact on the emission estimate. The exceptions being PT1, which will always be biased low, and PT2, which can be biased if some types of sites have more data than others. Spatial extrapolation methods for PSN showed more variability across methods. For both measurement systems, we also generally see that the more complex the extrapolation approach, excluding PT1, the lower the estimated emission rate (i.e., AT3 < AT2, PS3 < PS2, etc.). This result may not be generalizable and could look different if other extrapolation methods were considered.

3.5. Limitations

Since the amount of time the sites are monitored with the aerial survey is so limited, the annual emissions inventories based on the temporal extrapolations will vary greatly depending on the distribution of emission rates seen on the survey. Specifically, a modeling study estimated naïve scaling of semi-annual measurements would result in an average of between 18% and 48% sampling error, depending on the duration of intermittent events.[64] It is also possible PSN may miss or underestimate certain sources that aerial surveys capture. The potential underestimation of ground-based measurements was discussed in depth in SI Section S1.2 of Sherwin et al.[19] PSN controlled release studies with large emission rates and in real-world settings have also reported emission size quantification underestimation of ~75% on average across several PSN.[47,65] Standard controlled release studies show the majority of estimates are within a factor of three of true emissions, though individual estimates can be biased low or high by over a factor of ten.[29,51,66] Importantly, these standard controlled release studies have also shown a gradual improvement in PSN performance over successive studies.

Contemporaneous comparisons of aerial survey and PSN data may clarify potential causes for any differences between the two, especially if available at the source level where supervisory control and data acquisition (SCADA) can also be compared.[10] However, this type of reconciliation and cause analysis work is beyond the scope of this work. SCADA and/or PSN data could also be used to inform more complex, but more appropriate methods of temporally scaling aerial survey data that accounts for intermittent events, while aerial surveys can provide an independent point of comparison for PSN. This has been discussed as a necessary next step to best utilize these complementary measurement techniques in several recent works.[10,40,61,64] However, direct reconciliation between these measurements is not feasible at the annual scale as presented here.

3.6. Challenges in Aligning with Operational Realities

The emissions monitoring and survey measurements were collected as part of ongoing operator LDAR efforts rather than the development of an MII. As a result, key decisions were driven by different priorities. These design choices, such as the aerial survey strategy of revisiting emitting sites, produce analytical challenges and limitations for estimating comprehensive emission inventories. Fundamentally, the data collected from aerial surveys and PSN technologies do not have complete coverage spatially, temporally, and across the emissions rate distribution, and therefore, extrapolation is necessary to obtain an estimate of annual emissions. Importantly, such a challenge is likely to exist across operators prioritizing LDAR and treating the creation of an MII as a secondary benefit.

Current protocols and guidelines, such as Veritas,[34] OGMP 2.0,[36] and MiQ[35] provide insufficient guidance for operators concerning the extrapolation methodologies needed to develop an MII, particularly given the likelihood that data was not collected specifically to develop an MII. The representativeness and accuracy of an emissions inventory are a function of how comprehensively the data covers the relevant dimensions and the analytical methods used to process the data. With the current state of monitoring technologies, extrapolation methods are necessary to develop a credible, comprehensive inventory from measurement data. While advanced extrapolation methods often result in the most accurate estimates, operators lack guidance on the impact of various extrapolation methods on resulting MIIs and the tools and best practices to implement more accurate extrapolation methods. As such, operators must make assumptions regarding the emissions, and different assumptions will lead them to different extrapolation methods. This work begins to address these gaps and shows how these different underlying assumptions can impact the estimated emissions.

3.7. Implications and Future work

Interpreting estimates of emissions inventories and comparing estimates across basins or over time is difficult without uncertainty estimates provided alongside the point estimates. Accurately quantifying uncertainty in the measurement-based inventories outlined here will be the focus of future research. Two key learnings from this work are (1) that the choice of extrapolation method can greatly impact inventory estimates and therefore careful consideration of assumptions underlying these methods is warranted, and (2) there are significant barriers to performing reconciliation between some monitoring technologies and calculated inventories at the source level (e.g., between PSN and Subpart W). While this work is based on a single dataset, these key learnings are generalizable, given they are rooted in the underlying assumptions and mathematics associated with different extrapolation methods. The extrapolation methods presented here were applied to one dimension of coverage at a time (e.g. spatial, temporal, or emissions size), and therefore, they needed to be layered to arrive at a comprehensive emissions inventory. More advanced statistical methods could be constructed to perform extrapolation simultaneously across multiple dimensions. Such methods would be able to more accurately model individual site emission profiles and capture temporal correlation from one year to the next. This is an area of future work.

Notes

The authors declare no competing financial interest.

Supporting Information

The following files are available free of charge.

A full description of the methods used to anonymize the datasets used in this work (Text S1); A brief description of an alternative method used for linear temporal extrapolation of PSN data in cases without a measured endpoint (Text S2); Histogram of the percentage of time periods for PSN A that are periods of no information (Figure S1); Percentage of time periods for PSN that are unmonitored and periods of no information by site (Figure S2); visualization of the PSN A temporal extrapolation methods (Figure S2); detailed breakdown of all variables used in the multivariable prediction model used in the PSN spatial extrapolation partitioned by vendor and unmonitored periods (Table S1) (PDF).

Anonymized data and processing code is available through GitHub (https://github.com/yroell-gti/operator_mii_extrapolations).

Abbreviations

CH_4, methane; EPA, Environmental Protection Agency; GHGRP, Greenhouse Gas Reporting Program; GHGI, Greenhouse Gas Inventory; BU, bottom-up; TD, top-down; POD, probability of detection; PSN, Point Sensor Networks; LOD, limit of detection; SI, Supporting Information; GML, Gas Mapping LiDAR; MII, measurement-informed inventory; OGMP, Oil and Gas Methane Partnership; LDAR, leak detection and repair; MT, metric ton; AT, aerial survey temporal extrapolation method; PT, point sensor network temporal extrapolation method; PS, point sensor network spatial extrapolation method; BOED, barrels of oil equivalent per day; SCADA, supervisory control and data acquisition.

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Supporting Information for:

Extrapolation Approaches for Creating Comprehensive Operator-level Measurement-Based Methane Emissions Inventories

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This document contains 6 pages with 2 text sections (Text S1 – S2), 3 figures (Figure S1 – S3), and 1 table (Table S1)

Text S1. Anonymization Method

The anonymized data used in this work are noised versions of real data collected in 2023 from a dry-gas basin that has been shared by our operator partners. To anonymize the data, we assign each site a randomly selected scaling factor drawn from a common distribution. Individual data values (e.g. point sensor network (PSN), aerial, production) are then multiplied by a randomly generated datapoint-specific scaling factor closely centered around the site-specific value in a way that allows individual data values to be increased or decreased. This preserves important features (e.g., missing values, skewed distribution) and relationships (e.g., temporal correlation) while making the true values unrecoverable by a third party.

Text S2. Linear Temporal Extrapolation

The main text discusses using linear interpolation for periods of no information. If there is a period of no information at the beginning or end of the dataset (not including unmonitored periods), then there are not two data points to interpolate between. This was handled by extrapolating the measured endpoint throughout this period of no information as a constant. An alternative was tested where the missing endpoint is assumed to be zero. Although these approaches could result in significantly different results in some cases, for the randomly selected 50 sites, the difference in the total emissions was minimal (without accounting for unmonitored months, PSN A data: 108 MT CH_4 vs 109 MT CH_4; PSN B data: 342 MT CH_4 vs 342 MT CH_4).

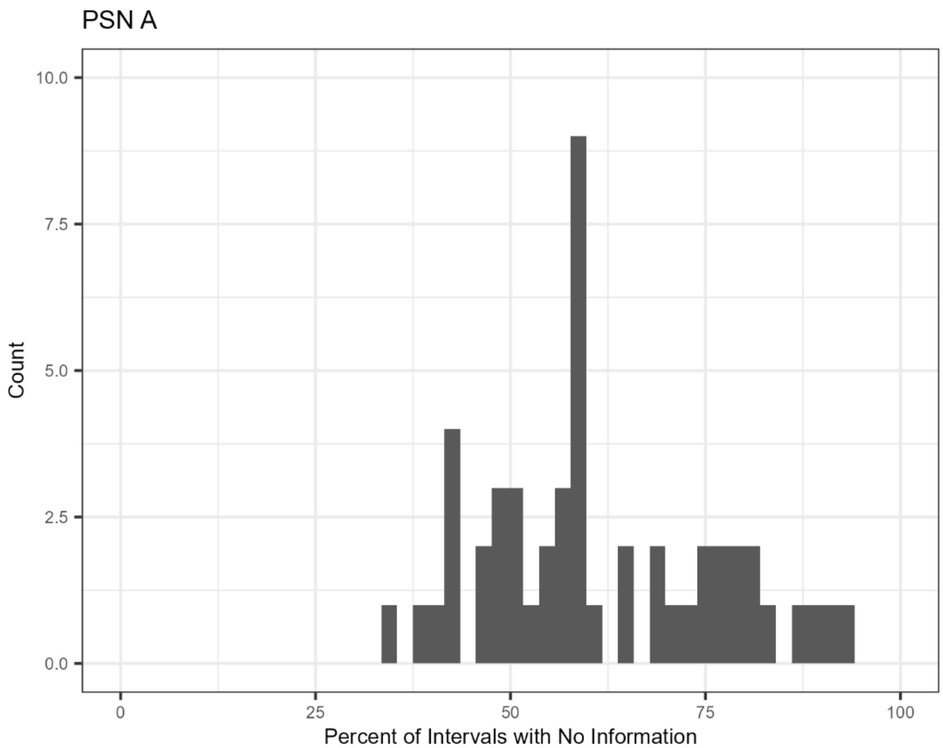

Figure S1. Percentage of 15-minute intervals with emission rate originally reported as missing (period of no information) for sites monitored by PSN A.

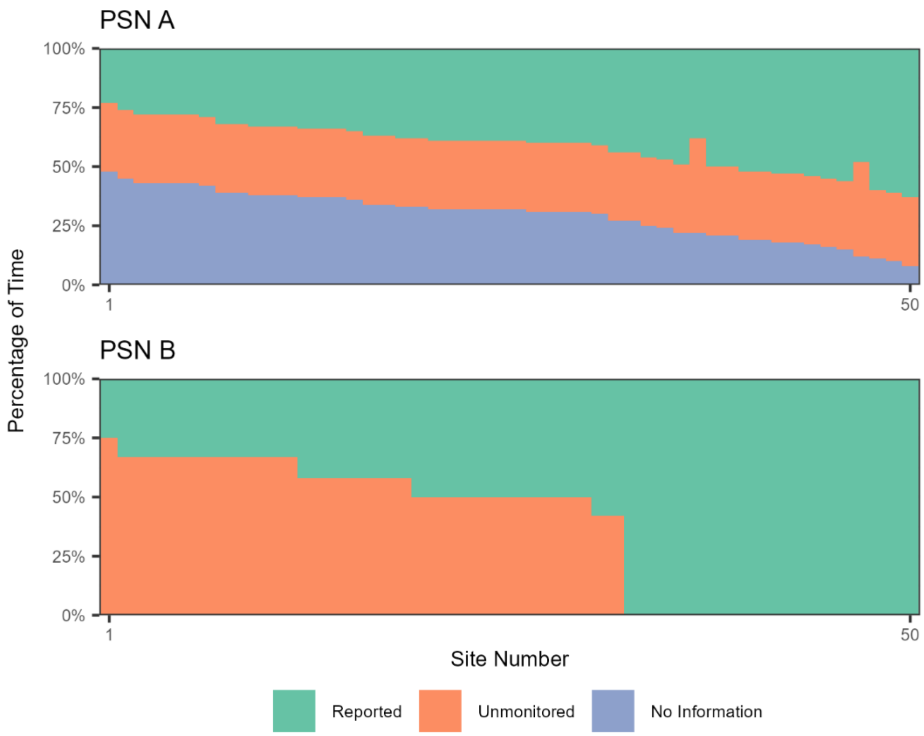

Figure S2. Percentage of time during 2023 for each site when the site was unmonitored, there was a period of no information, and the PSN reported an emission rate. Based on the originally reported data.

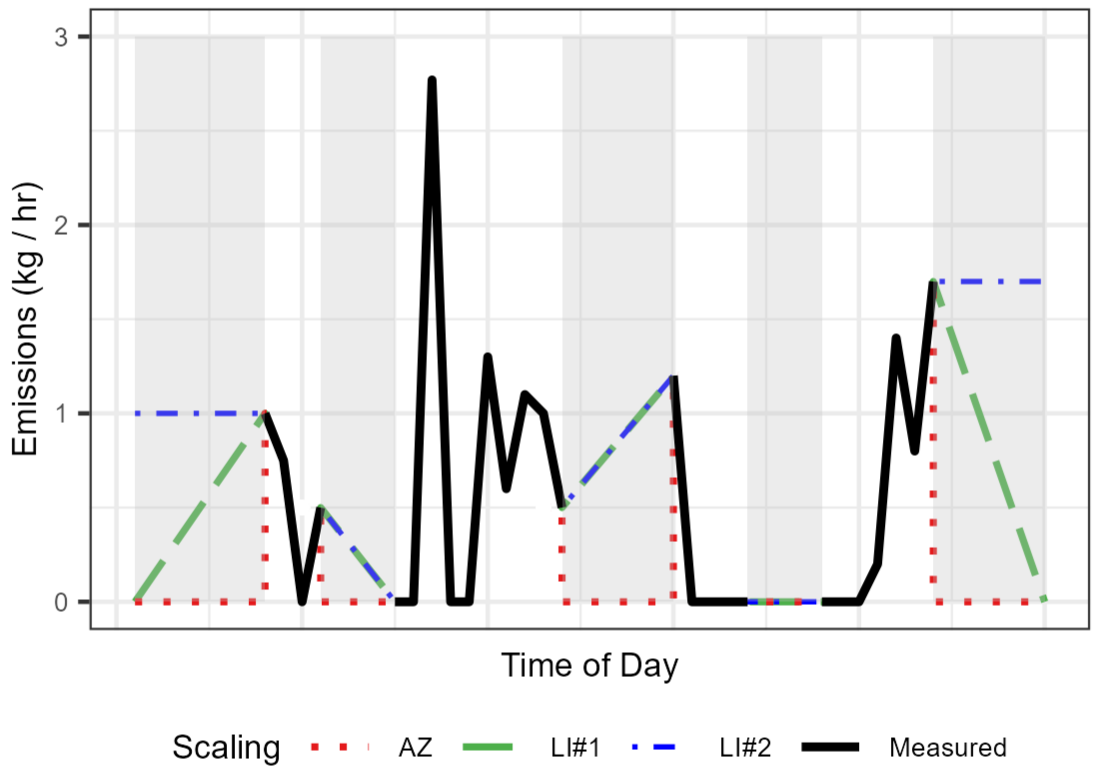

Figure S3. Temporal extrapolation methods applied to simulated data, with five periods of no information (denoted by the grey bands) used to illustrate the effects of the different methods. The measured data is denoted in black. The extrapolation methods shown include assuming all emission rates during periods of no information are zero (AZ = all zero; red),linear interpolation between observed emission rates on either side of the period of no information and assuming missing endpoints are zero (LI#1 = linear interpolation method 1; green), and extrapolating a constant on the boundary period of no information (LI#2 = linear interpolation method 1; blue). The naïve scaling methods (2 and 3) are not shown as they are performed on the aggregate total emissions.

Table S1. Site characteristics for those with PSN and those without PSN. Production is reported in barrels of oil equivalent per day (BOED).

Site Characteristic	PSN A (50)	PSN B (50)	Unmonitored (100)
GHGRP Reported Emissions (Tonnes CH_4)			
% reported as zero	24%	4%	19%
Median emissions (w/o zeros)	1.1	3.0	1.2
Production (BOED)			
% reported as zero	4%	0%	5%
Median production (w/o zero)	1253	1335	119
Production Strata (%)			
Inactive/No Data (0 BOED or NA)	4%	0%	5%
Marginal (1-15 BOED)	12%	0%	40%
Standard (16-300 BOED)	48%	60%	53%
High (>300 BOED)	36%	40%	2%
Age (Years)			
Median age	10	6	13
PSN Emissions (Tonnes CH_4)			
Median annual emissions	0.2	0.3	NA