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Creating Accurate Methane Emission Inventories through Data-Driven Airborne Survey Strategies#

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ABSTRACT

Because natural gas emits less carbon than other fossil fuels, it holds promise as a green energy transition fuel. However, the overall carbon footprint of natural gas is significantly elevated by methane emissions that occur during its production and transmission (Cusworth et al. 2022). Methane "super-emitters," while comprising only about 1% of sites, are responsible for the majority of oil- and gas-sourced methane emissions, making their detection and mitigation critical in reducing the climate impact of natural gas and in meeting national and global sustainability goals (Sherwin et al. 2024). Yet, despite advancements in detection, significant uncertainties remain regarding the size, frequency, and duration distributions of methane emissions (e.g., Frankenberg et al. 2016, Cusworth et al. 2022, Chen, Sherwin et al. 2022, Conrad et al. 2023, Johnson et al. 2023, Sherwin et al. 2024) underscoring the need for comprehensive emissions inventories segmented by basin across the US. Airborne surveys are well-suited for collecting data to build these comprehensive, basin-level inventories because they allow for extensive spatial coverage, and have the spatial resolution, and the sensitivity to pinpoint individual methane sources. As remote sensing technologies enable rapid basin-scale surveys, it is imperative to establish scientifically and statistically robust standards to generate reliable and actionable emissions inventories.

Recent work has shown that differences in airborne sampling strategies, detection technologies, and analysis can lead to large differences between survey conclusions if not correctly accounted for (Chen et al. 2024). This elevates the importance of incorporating proper sampling and analysis techniques when designing a methane emissions monitoring campaign to produce accurate results and facilitate cross-study comparisons. In this paper, we describe a survey strategy designed using the latest conclusions from the literature to align results from different aerial surveys. We identify several sampling and analysis principles, including large sample sizes, balanced sampling across oil and gas production, careful survey area definition, and a unified protocol for analysis, to be vital to producing an unbiased estimate of basin-scale emissions. We present results from a Department of Energy-funded project that deployed this survey strategy in two understudied oil and gas-producing regions in the United States: the Haynesville Basin in Texas and Louisiana, and the Woodford Shale in the Anadarko Basin in Oklahoma.

Keywords: methane emissions, oil and gas, mitigation technologies, survey strategy, cross-comparison

1. INTRODUCTION

Over the next 20 years, a projected 6+ billion tons of anthropogenic methane emissions will result in up to 0.5°C of global warming (Szopa et al. 2023). This warming potential highlights the urgent need for targeted strategies to mitigate these emissions, particularly in the oil and gas (O&G) sector, which accounts for about one-third of these emissions in the United States (Maasakkers et al. 2016). Methane "super-emitters" – defined here as emissions with instantaneous rates larger than 10 kg/hr

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– occur only at about 1% of well sites in the O&G sector but are responsible for a disproportionate >50% of the overall emissions volume (Sherwin et al. 2024). Many of these emissions are unintentional, stemming from

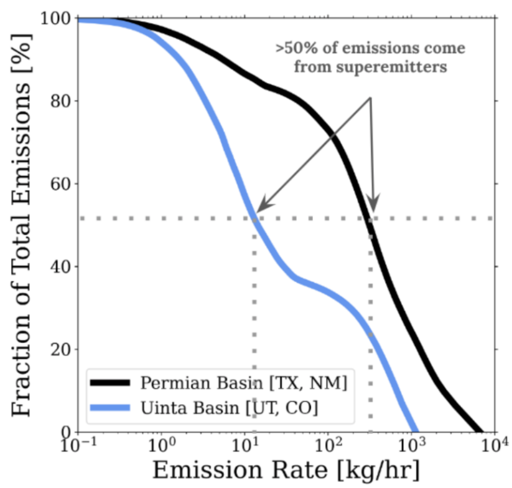

Fig. 1 Cumulative fraction of total emissions as a function of emission rate per site for two basins from Sherwin et al. (2024).

operating conditions such as equipment breakdowns and failures (e.g., Rutherford et al. 2021). These fugitive emissions can therefore be addressed through repairs and improved technologies and practices. However these rare emissions must first be located, and their size and occurrence frequency characterized.

Consequently, there is a critical need for basin-specific methane emissions inventories to identify and inform efficient leak detection and mitigation strategies and provide a basis for developing future survey strategy. Recent studies (e.g., Cusworth et al. 2022, Chen, Sherwin et al. 2022, Sherwin et al. 2024) have demonstrated the importance of capturing the heavy-tailed (non-Gaussian) distribution of super-emitters for informing inventories, which requires scalable remote sensing measurements that are of adequate spatial resolution to associate emissions with facility-level sources. With rapid advancements in methane detection technologies and complementary regulation incentivizing methane emission mitigation, there is a promising opportunity for generating large, basin-scale surveys that can inform emission inventories and optimize methane emission reduction strategies.

Recent work has shown that differences in airborne sampling strategies, detection technologies, and analysis protocols can lead to considerable differences between survey conclusions if not rigorously accounted for. **As new remote sensing technologies enable rapid, basin-scale surveys, it is critical to establish scientifically and statistically robust standards to generate reliable and actionable emissions inventories.** In this paper, we synthesize the latest airborne survey strategy recommendations from the literature and share results from two surveys designed to provide emissions inventories for two key O&G basins in the US that will help inform optimal methane emission mitigation strategies.

2. METHODS

2.1 Survey sample size is critical to capture the full emissions distribution

A recent study (Sherwin et al. 2024) combining Insight M and Carbon Mapper aerial remote sensing data with bottom-up simulations of emissions finds that only 0.05%-1.44% of sites contribute more than 50% of the overall emissions via super-emitter sources across basins (Figure 1). Basins with different levels of production appear to have varied frequencies of super-emitters, but the overall picture is clear: more than 50% of emissions are contributed by these large, infrequent sources.

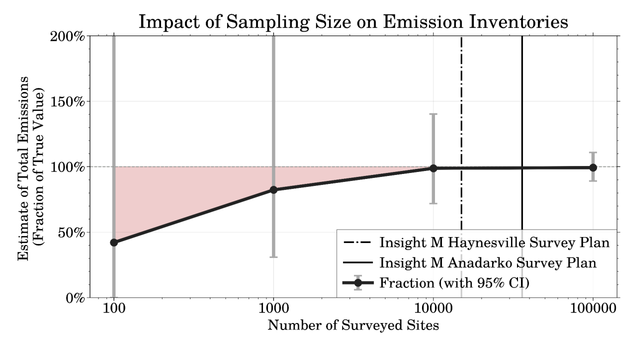

Fig. 2 Median and 95% CI in emissions estimates from subsampling 98,000 sites in Chen, Sherwin et al. (2022)

Since super-emitters are rare, surveys with smaller sample sizes can fail to capture them, which can lead to a significant underestimation of total emissions and a misrepresentation of the emissions distribution. Figure 2 highlights the importance of survey sampling using results from the Permian basin in the US (Chen, Sherwin et al. 2022). Chen et al. performed Monte Carlo simulations showing the bias and variance in estimated total emissions at different sample sizes by subsampling Insight M airborne survey data of 98,000 sites in the New Mexico Permian basin. At 100 sites sampled, the median

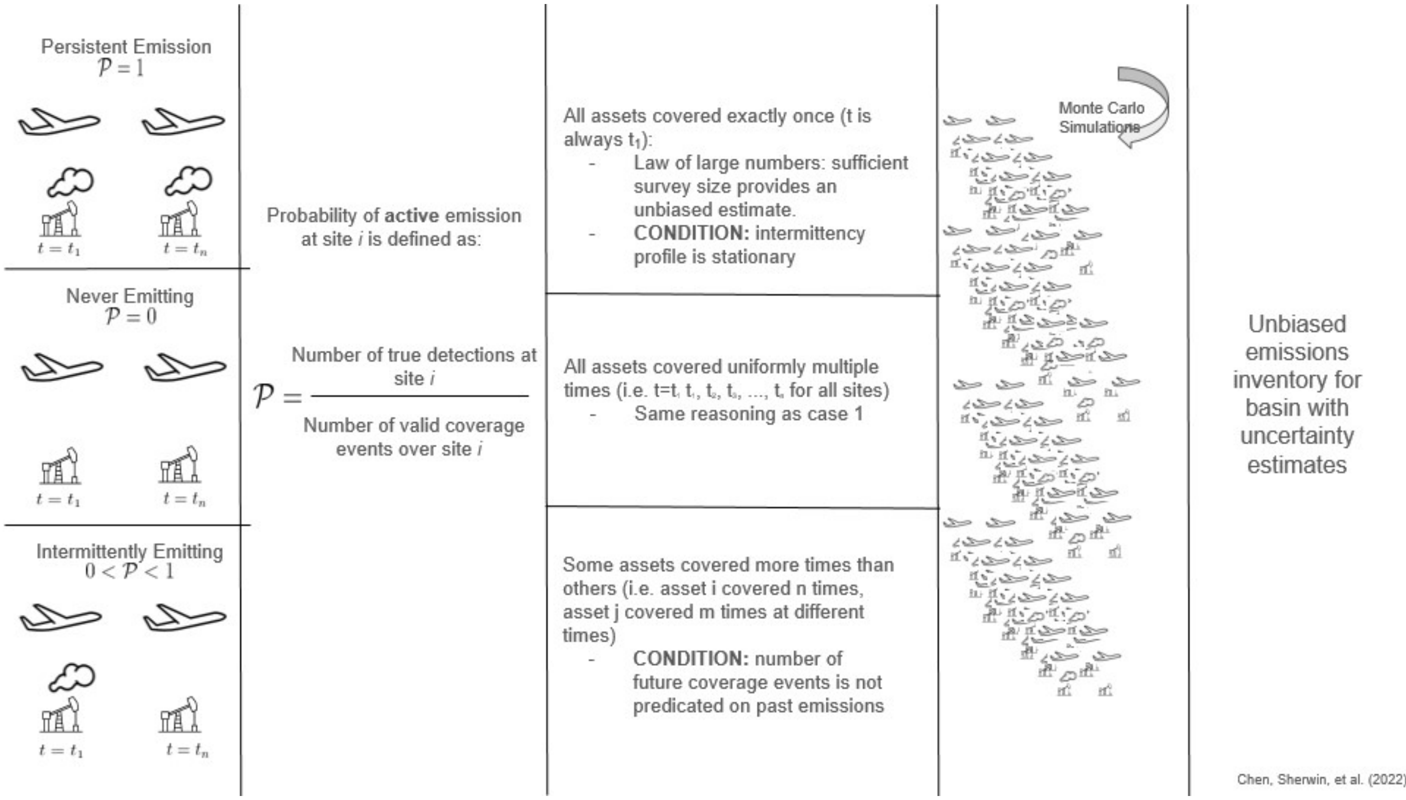

Fig. 3 Airborne surveys with spatiotemporally uneven sampling can yield unbiased estimates of the emissions inventory of a basin. The left panel illustrates three possible scenarios for site emissions when surveyed at different times: (1) persistent emissions, (2) no emissions, and (3) intermittent emissions. The center panels demonstrate modeling this system as a Bernoulli process, outlining the conditions under which airborne surveys can provide unbiased and precise total emissions estimates. The right panel shows that Monte Carlo sampling is used in the analysis protocol to quantify uncertainties in the emissions estimates.

of total emissions prediction significantly underestimates the emissions (only ~35% of the true value) from the full study because it does not adequately capture the impact of super-emitters. At 1,000 well-site measurements, the median estimate improves to ~80% of the full study value, indicating better characterization of the distribution's tail, yet it still misses significant emissions and exhibits a wide 95% confidence interval (30.8% - 215.5% of the true value). At 10,000 sites and 100,000 sites sampled, the estimate is consistently much closer to the full study estimate, demonstrating that larger sample sizes are critical to capturing an unbiased and precise view of basin-level emissions.

An additional complication in designing methane emission survey strategies is that the duration of super-emitters can vary from minutes to years. Moreover, the distribution of these emission durations can vary by basin. Current technologies lack the sensitivity and scalability to continuously monitor every asset across these basins. However, this technological shortcoming can be overcome by ergodic sampling, which produces a representative distribution by obtaining many independent realizations. The result is equivalent to measuring the system for an extended period of time and overcomes uncertainty resulting from emission sources with varying durations.

In light of the challenges of detecting super-emitters and understanding their duration, there are several important analytical considerations for developing emissions estimates using aerial surveys. Figure 3 shows a flowchart demonstrating the conditions under which large sample-size surveys provide unbiased estimates of the overall emissions in a basin even if they are conducted at irregular temporal intervals and with varying frequency of spatial coverage. In particular, intermittency is accounted for by modeling the presence or absence of emissions as a Bernoulli process, where the probability of active emission at site *i* is defined as shown in the center-left panel of Figure 3. This treatment of intermittency will yield unbiased estimates of the emissions distribution under two conditions: (1) the intermittency profile of emissions is stationary over space and time at basin-wide scales, and (2) future coverage events are not predicated on past emissions (center-right panel of Figure 3).

In the case studies presented here, the uncertainty in the quantification of methane emissions from the surveying instrument and the treatment of intermittency are rigorously propagated via Monte Carlo sampling to finally create a total emissions estimate with uncertainty (e.g., Chen, Sherwin et al. 2022, Johnson et al. 2023, Sherwin et al. 2024). To account for the survey instrument's partial detection range, each Monte Carlo realization identifies undetected emissions within the partial detection range by binning emission rates into even intervals. The number of undetected emissions in the partial detection range is then estimated based on independent instrument probability of detection curves, and their contribution can be added to the emissions inventory.

2.2 Building a representative survey area

In addition to collecting measurements from a large number of sites, aerial surveys must also be designed taking into consideration differences across sites. This can be achieved through site stratification. Stratification creates groups ("strata") of sites such that sites within a group are similar and groups of sites are different from one another. Characteristics such as oil-rich vs gas-rich, owner/operator, age, location, site production, and the site's position within the industry (upstream or midstream) are important features to consider. Recent work (Sherwin et al. 2024) has found quantified methane loss rates to vary significantly between different sub-regions of the Permian basin by almost a factor of two when surveying different productivity profiles. Stratifying sites (e.g., Johnson et al. 2023, Sherwin et al. 2024) by these features and sampling sites from each group can ensure that the sample is representative of the entire basin.

In building the survey strategy for the ongoing DOE project, we queried asset data for producing wells in addition to monthly production records for those wells from Enverus' well life cycle datasets. We used total energy production from these data sets to determine the productivity and balance of production mix of the two basins and our proposed sample areas. Important considerations here are the quality and consistency of production data as well as the ability to evaluate oil, gas, and total energy productivity for all assets in areas of analysis. Enverus' well life cycle datasets are regularly updated, cleaned, and maintained to provide standardized information across active basins and plays. This standardization allows one to better compare basins to sub areas to evaluate the representativeness of selected samples. Alternative data sources such as state-maintained databases can be used to perform similar analysis.

Furthermore, using well-defined spatial definitions of basins, shales, or plays and transparently sharing these defined areas is critical for allowing alignment and consistency across research studies and ensuring that the underlying production of assets within those areas is carefully considered when comparing total emissions estimates across studies. For this reason, we used publicly available definitions from the U.S. Energy Information Administration (EIA) to define the Haynesville and Anadarko Basin boundaries to use for defining sample areas. We also used EIA definitions to inform our boundary of the Woodford Shale and determine sampling areas within it.

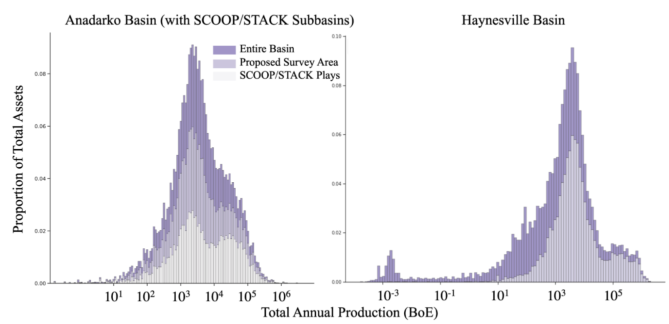

Fig 4. Planned survey areas production characteristics compared to the overall basin for ongoing Insight M airborne surveys in Anadarko and Haynesville basins.

Within the boundaries defining the sampling region, it is important to carefully evaluate asset infrastructure data to develop candidate sites for sampling. While there is no fully comprehensive dataset of asset infrastructure due to reporting limitations, it is important that infrastructure datasets utilized cover the study area and that they are not biased towards any subset of operators. Ideally, whether manually or through third party data sources, infrastructure datasets should be pooled from all relevant levels of reporting and processed such that essential attribute information like operating statuses and productivity are standardized for use in identifying relevant infrastructure for sampling. For production infrastructure we use Enverus' well life cycle datasets, and for midstream pipelines and facilities we use Hart Energy infrastructure data. Both sources and the respective datasets from each are standardized and maintained regularly with data covering all available infrastructure across operators and basins.

Despite this standardization, some O&G infrastructure is less well documented or complete than others, particularly midstream facilities. For example Sherwin et al. (2024) showed that up to 1/3rd of total emissions volume could be attributed to sometimes poorly mapped gathering lines. For this reason, it is even more imperative to conduct careful and comprehensive area-wide sampling to ensure representativeness of surveyed infrastructure. Working with near-complete basin-level infrastructure datasets, filtered by well-defined boundaries, and filling in areas between assets helps to avoid unintended gaps in sample asset coverage which enables better O&G segment classification of detected emissions and their representativeness of the entire basin.

3. EARLY RESULTS

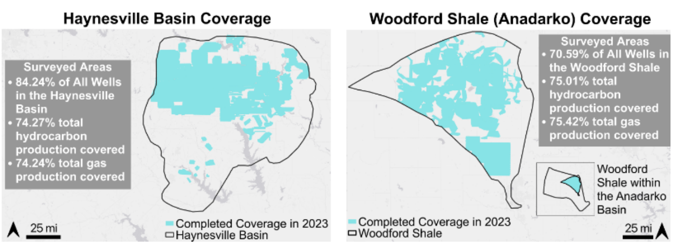

Fig 5. Early results from Insight M's ongoing airborne surveys in the Haynesville and Anadarko basins

Figure 5 shows the areas that have already been surveyed in the Haynesville and Anadarko basins as part of a three-year DOE-funded collaboration between Insight M, MiQ, LBNL, Stanford, and GHGSat. The careful survey planning described above is complemented by a unified protocol for analysis that is aligned with the Veritas approach (GTI Energy 2023). This includes analysis of emission duration using data from multiple methane emission surveys and reconciliation with bottom-up emission estimates. We divide emissions into two categories: best measured and best modeled as suggested by the Veritas protocol. The prior group includes all emissions sources that have rates sufficiently large to be detected by the Insight M LeakSurveyor. We model emissions too small for our sensor to detect through stratified random sampling of site-level emissions generated from updated emission factors (Rutherford et al. 2021, Zimmerle et al. 2022). We then follow a Monte Carlo approach to yield a reconciled total emission rate at each site and for the basin as a whole.

4. DISCUSSION & CONCLUSIONS

In this paper, we demonstrate the importance of data-driven survey strategy to create accurate estimates of basin-scale methane emissions:

1. Sample size is key. Spatially comprehensive airborne surveys are crucial for creating accurate estimates of basin-scale methane emissions by adequately capturing the importance of super-emitters – rare, but important emissions that are only effectively accounted for with large sample sizes.
2. We show that under certain conditions, survey sampling can be considered an ergodic process, which allows independent, discrete observations from airborne surveys to make statistically robust inferences about the overall emissions dynamics despite the high levels of intermittency of many oil field methane emissions.
3. Large, frequent surveys can show bias if the geographical and physical characteristics of the basin are not adequately considered, especially across production variability (e.g., Sherwin et al. 2024). In the ongoing DOE project to survey two understudied basins in the US, we highlighted the rigorous data quality and statistical checks performed to ensure that the top-down estimates that will be derived from this study will be robust.
4. The importance of spatially comprehensive surveys is further magnified when considering that some O&G infrastructure is poorly mapped and can be a large contributor to the overall emissions volume. Spatially comprehensive surveys help adjust for incomplete asset data, while multiple sources of asset data can be pooled to improve understanding of covered assets.
5. Moreover, we highlight the need for a unified analysis protocol in the reconciliation of top-down and bottom-up emission inventories.

In conclusion, airborne surveys with extensive, statistically robust sampling, carefully defined spatial boundaries, and unified analysis protocols are essential for creating accurate emissions inventories across basins, which can then inform the most effective methane mitigation strategies.

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