Estimating oil and gas methane emissions: why skewness is a challenge

William Daniels[1], Michael Basanese[2], Dorit Hammerling[2]

[1]Department of Environmental Health and Engineering, Johns Hopkins University, [2]Department of Applied Mathematics and Statistics, Colorado School of Mines

Key Results

1. *Very large samples (>50% of the basin) may be required to mitigate sampling error if super-emitters are large and rare.*
2. *Differences in emission characteristics between basins necessitate basin-specific sampling strategies.*

1. Introduction

- Voluntary reporting programs (e.g., OGMP 2.0) and upcoming regulatory initiatives (e.g., EU import rules for LNG) mean that efforts to measure oil and gas methane emissions are not going away.
- To date, there are no definitive standards for how to conduct a measurement campaign that robustly characterizes methane emissions. A key open question is: **how many sites do you need to measure?**
- Answering this question is complicated because methane emissions follow extremely right-skewed distributions. Samples from these distributions do not behave in the same way as samples from "well behaved" distributions with minimal skew (e.g., the normal distribution). Ignoring this fact can cause large errors in any analysis that follows a methane measurement campaign, such as creating measurement-informed emissions inventories for reporting purposes.
- **Therefore, we aim to: 1) quantify the errors that result purely from sampling variability under extreme skewness, and 2) provide sample size guidance for future methane measurement campaigns that bounds these errors.**

2. Materials and methods

- Treat two state-of-the-art emission rate distributions from the literature as "true" population distributions in six US oil and gas basins.
  - *Williams et al. (2025)*: methane emission rate distributions based on ground measurements with low detection limits (<1 kg/hr).
  - *Sherwin et al. (2024)*: methane emission rate distributions based on aerial measurements with higher detection limits (>10 kg/hr).

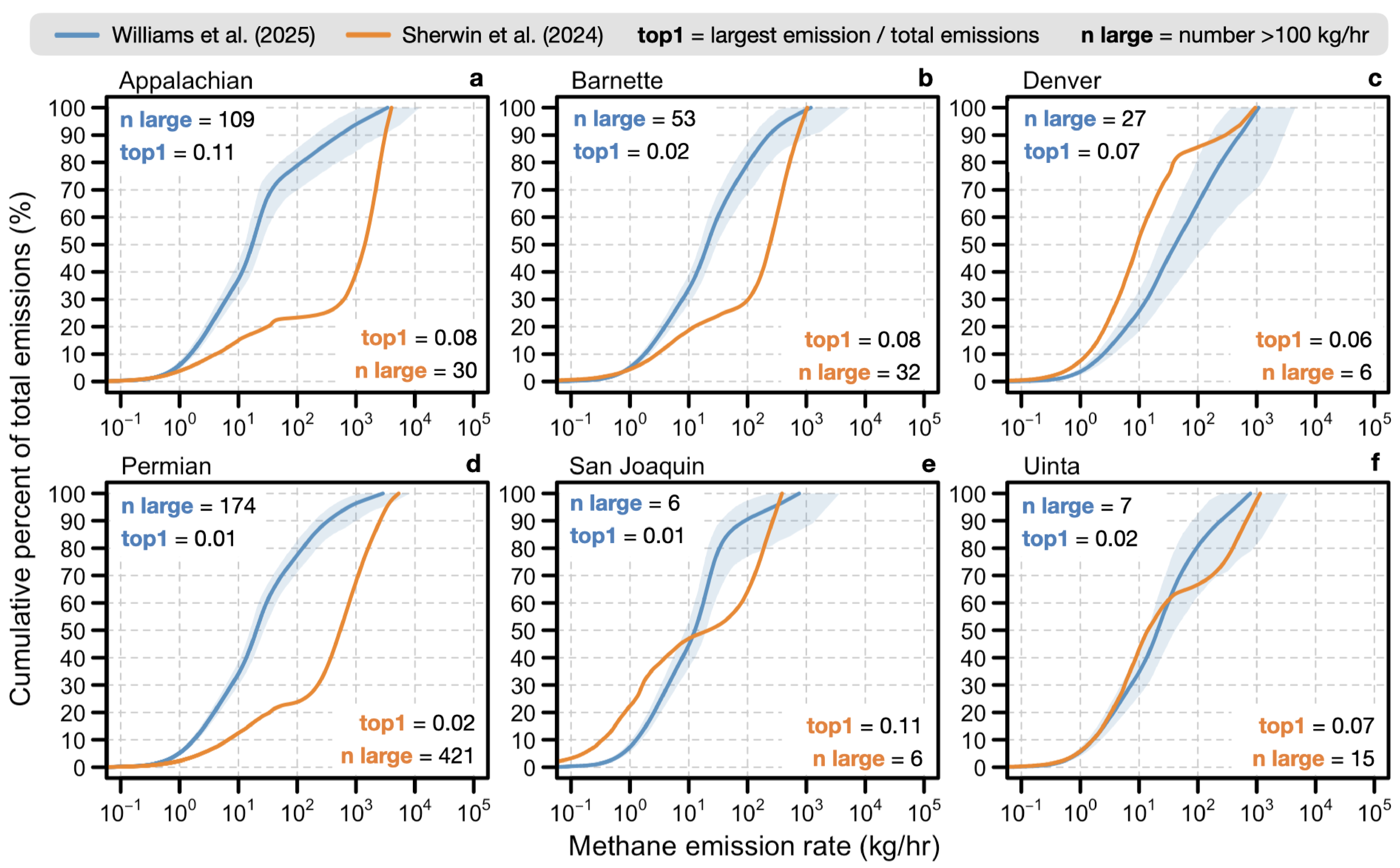

Figure 1: Basin-level emission rate distributions from Williams et al. (2025) and Sherwin et al. (2024) used as true population distributions in this study.

- Quantify sampling variability by resampling 1,000 times from the population distributions (without replacement) at sample sizes ranging from a single measurement to the size of the entire distribution.
- Compare the sample means to the true population mean using three metrics: 1) median error, 2) maximum error, and 3) probability of a single sample mean being within 10% of the true mean.

3. Illustration of sampling variability

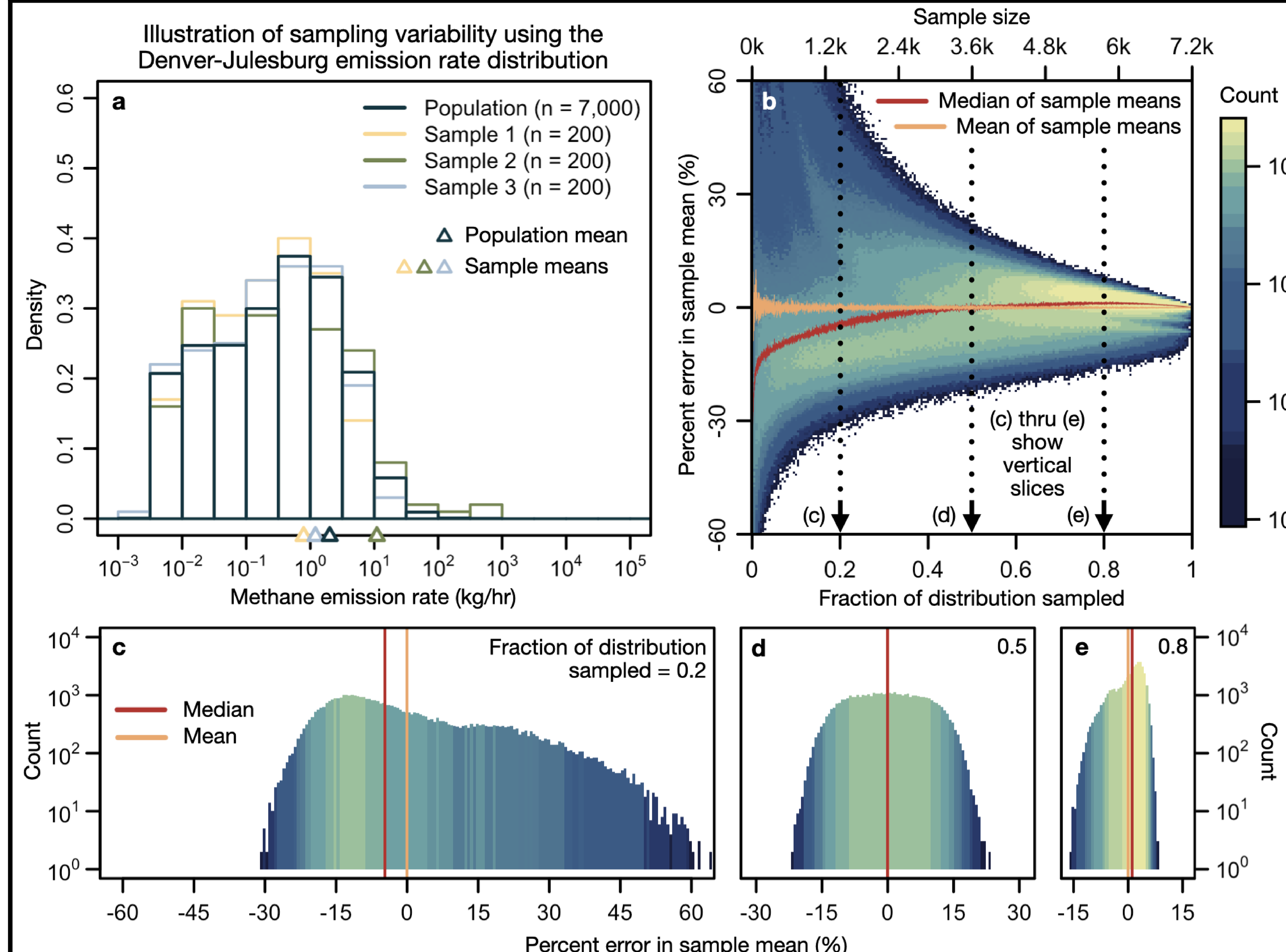

Figure 2: Illustrative example using the Sherwin et al. (2024) emission rate distribution for the Denver-Julesburg basin. (a) True population distribution and three samples. (b) Distribution of errors in the 1,000 sample means across sample sizes. (c) thru (e) Vertical slices of (b) as histograms.

- **Result #1:** Small samples that include rare super-emitters will significantly overestimate the true distribution mean, while the majority of samples that miss these large emissions will slightly underestimate. See Fig 2(a).
- **Result #2:** For highly right-skewed distributions, very large samples may be required to mitigate errors from sampling variability. Even when sampling half of the Denver-Julesburg basin, the 95% confidence interval on the average emission rate ranges from -15.0 to 15.3% of the true average and there is a maximum error of 23.0%. See Fig 2(d).

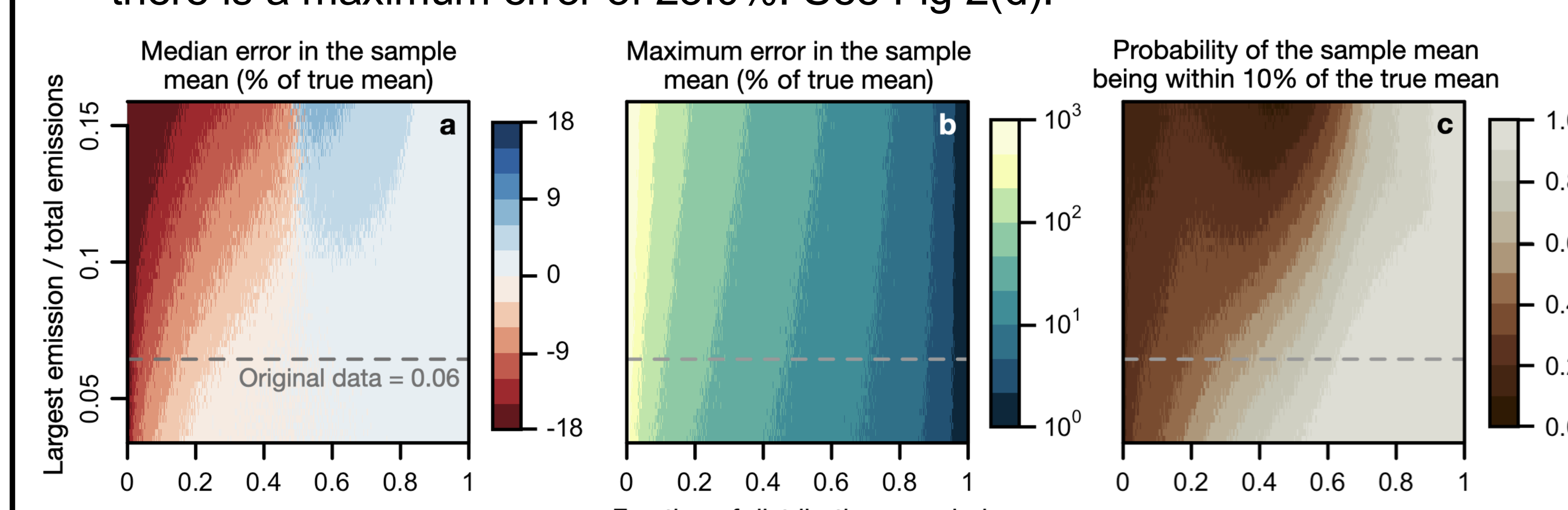

Figure 3: Three error metrics for the sample mean across a range of sample sizes using the Denver-Julesburg emission rate distribution. Vertical axis shows the influence of the largest emission in the population distribution. We manually adjust the largest value in this distribution for illustration.

- **Result #3:** Sampling variability is amplified by large, rare super-emitters.

4. Basin-specific sample size guidance

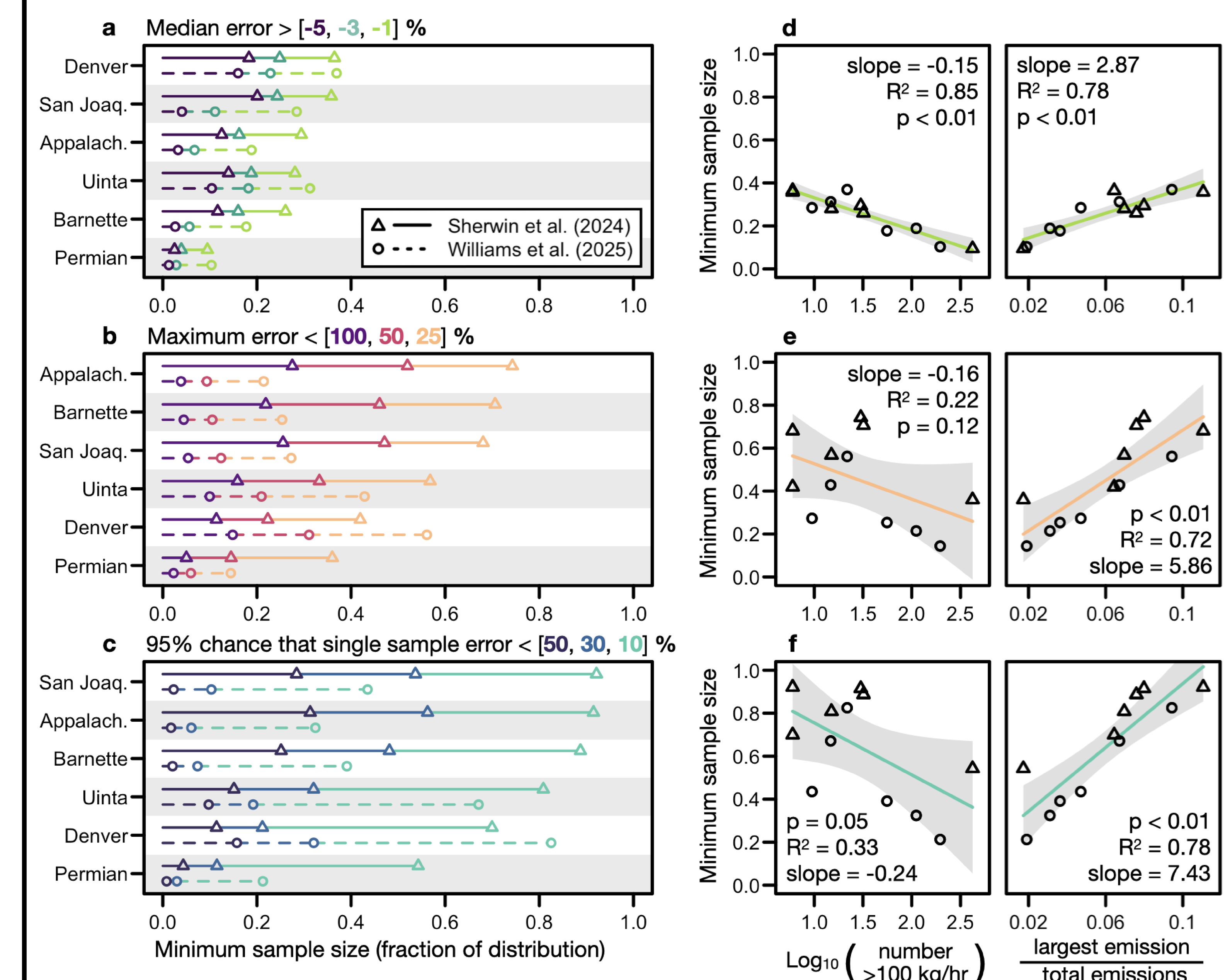

Figure 4: (a) thru (c) Basin-specific sample size guidance according to three different error metrics for the sample mean. Each point shows the minimum sample size required to satisfy the corresponding error threshold listed in the plot title. Correspondence between points and error thresholds is shown with color. (d) thru (f) Linear relationship between two features of the underlying emission rate distributions and the sample size required to meet the strictest error thresholds from (a) thru (c). Each point corresponds to a basin-level distribution from either Williams et al. (2025) or Sherwin et al. (2024).

- **Result #4:** Two features of the underlying emission rate distribution drive sample size requirements: the number of large emissions (>100 kg/hr) and the magnitude of the largest emission relative to total emissions. This is because super-emitters that are both large and rare make it hard to characterize average emissions (see Fig 3).
- **Result #5:** Basins with more super-emitters require smaller samples to accurately characterize average emissions. This has implications for measurement campaign design. For emission mitigation, allocate more measurements to basins with more super emitters, but for inventory development, allocate more measurements to basins with fewer super-emitters where they are harder to find.
- **Result #6:** Very large samples are often required to keep error in a single sample below 10% (at the 95% confidence level). This is an important metric for measurement campaign design, as each future campaign only provides one "sample" of the emission distribution.
- **Result #7:** Differences between the Williams and Sherwin emission rate distributions result in very different sample size requirements. More work is needed to reconcile these state-of-the-art estimates of methane emissions from the US oil and gas sector!

References

1. Williams et al. (2025). Small emission sources in aggregate disproportionately account for a large majority of total methane emissions from the US oil and gas sector. *Atmospheric Chemistry and Physics.*
2. Sherwin et al. (2024). US oil and gas system emissions from nearly one million aerial site measurements. *Nature.*