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Metrics and methods for determining uncertainty in measurement informed methane emission inventories due to spatial and temporal extrapolations

Methods and metrics for quantifying temporal and spatial extrapolation uncertainty from methane emissions from oil and gas operations

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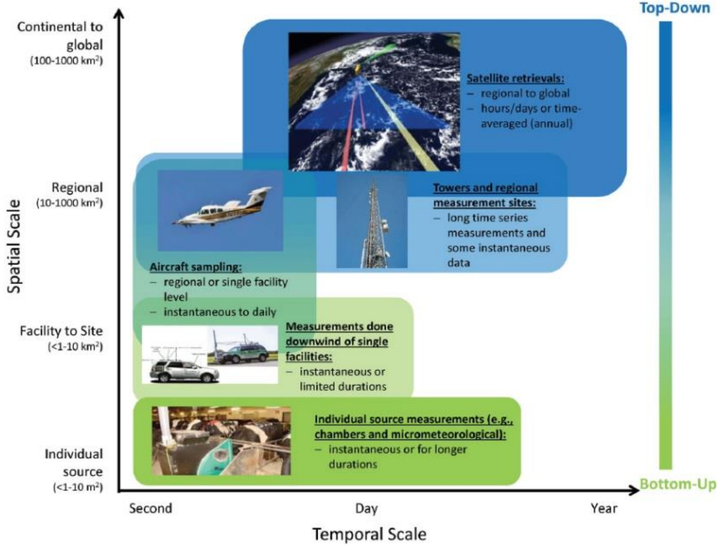
Introduction

Importance of understanding uncertainty in measurement-informed methane inventories

Voluntary and regulatory methane emission reporting initiatives are seeking to include methane measurements into annual inventory reporting guidelines for oil and gas facilities

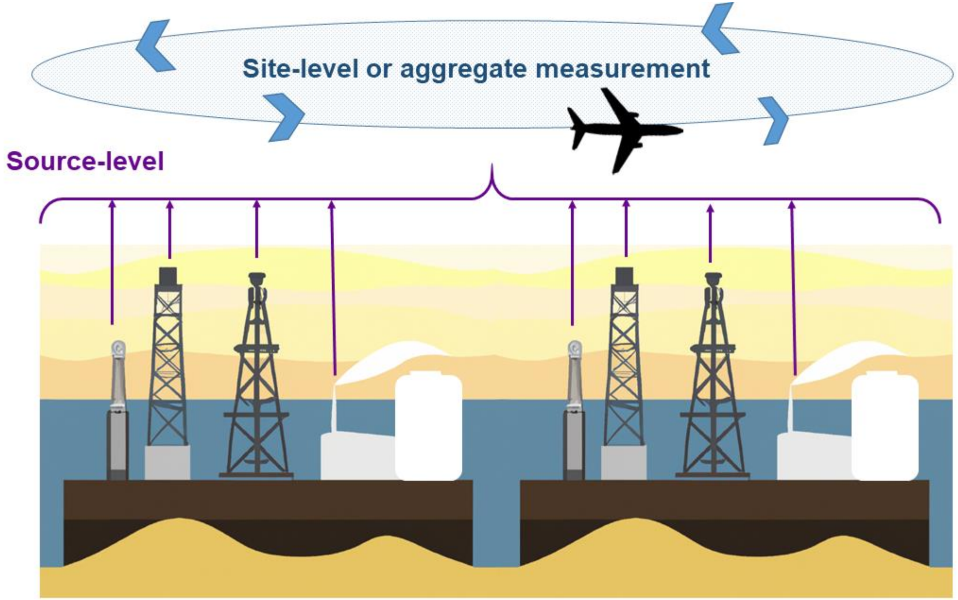
- Measurement technologies span varying spatiotemporal resolutions

- There are varying methods for how to incorporate these measurements into annual inventory estimates



National Academy of Science, Engineering, and Medicine (2018)

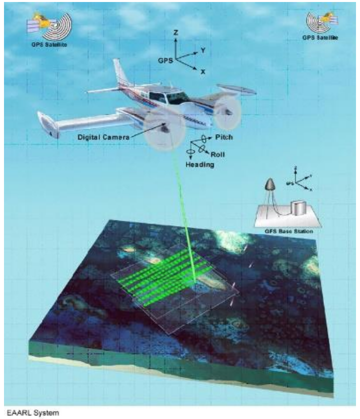
Measurements can be at the source-level or site-level



All methane measurements and measurement informed inventories have some combination of three different types of uncertainties

Measurement uncertainty

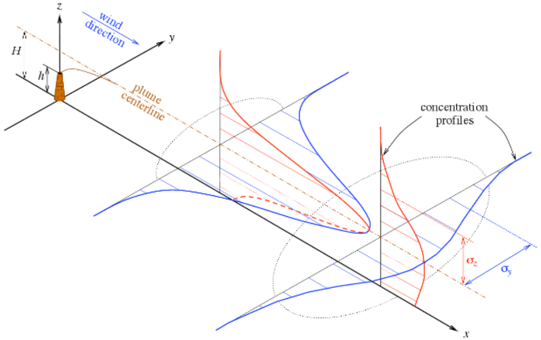
Uncertainty associated with primary measurement technique



U.S. Geological Survey (2014)

Emission rate uncertainty

Uncertainty associated with converting primary measurement with an emission rate estimate



Stockie, J. (2011)

Extrapolation uncertainty

Uncertainty associated with both
1) extrapolating short-duration measurements to a longer timescale and
2) extrapolating measurements from a sample population to an entire region

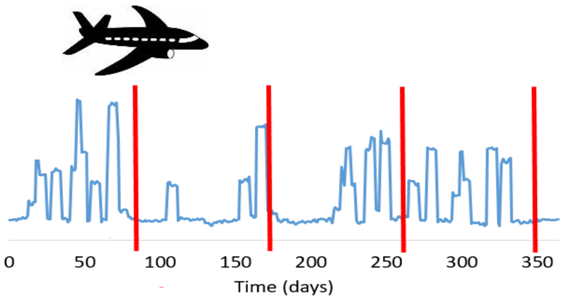
Google Earth (2023)

Temporal Extrapolation: The extrapolation involved with taking measurements with a limited amount of temporal coverage and scaling the results to a larger temporal scale

Spatial Extrapolation: The extrapolation involved with taking measurements from a limited number of sites or sources and scaling the results to a larger spatial region

Quantifying extrapolation uncertainty is necessary for designing effective measurement campaigns and conducting meaningful analyses from measurements. Using two case studies, this work develops metrics for selecting:

1.) Sample frequency



Schissel, C., Allen, D. T. (2022)

2.) Sample population

Peter Aengst (2015)

Case Studies & Methods

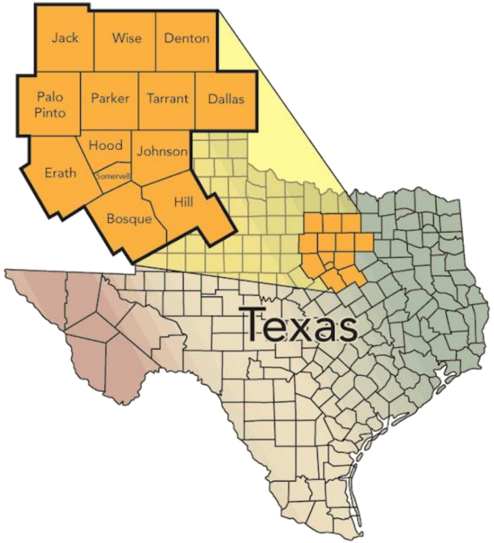
Barnett Shale, TX – Quantifying temporal extrapolation uncertainty

Green River Basin, WY – Quantifying spatial extrapolation uncertainty

Barnett Shale case study

The Barnett Shale is a natural gas production region in north central Texas

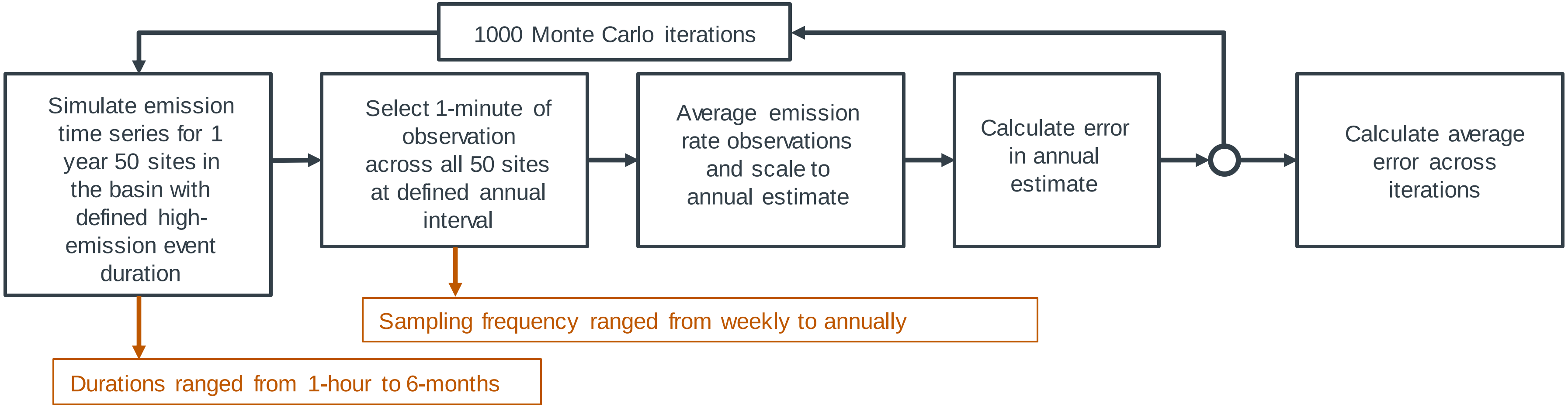
- Emissions from the Barnett Shale are characterized by a highly skewed distribution, with the highest-emitting 1% of sources contributing to almost half of total emissions



Oil and Gas Journal (2009)

Barnett Shale case study

The goal of this case study is to quantify the error that arises from temporal extrapolation, and to identify the variables that most significantly impact this error.



Barnett Shale case study

Temporal extrapolation uncertainty is significant and is dependent on the characteristics of emission events

Average annual inventory error as a function of sampling frequency and event duration

	Weekly	Monthly	Quarterly	Semiannually	Annually
1-hour	11%	23%	34%	45%	74%
6-hour	11%	22%	34%	48%	75%
1-day	10%	22%	34%	45%	70%
1-week	1%	20%	34%	46%	74%
1-month	3%	4%	30%	41%	71%
6-month	1%	4%	10%	18%	51%

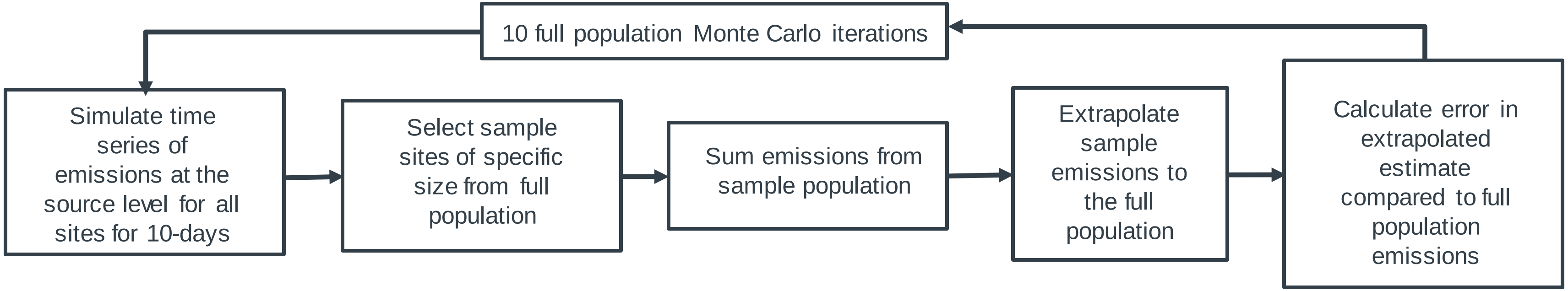
We define **duration ratio** is a metric relating emission event duration and sampling frequency, where duration ratio is defined as $\frac{duration\ of\ the\ event}{time\ between\ sampling}$

Duration ratio ≥ 1 leads to a significant decline in average error in comparison to scenarios with duration ratios <1

Schissel, C., Allen, D.T. (2022)

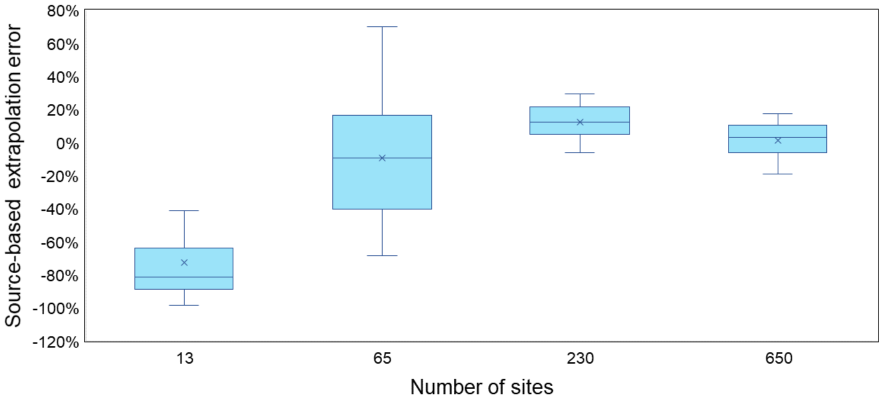
Green River Basin case study

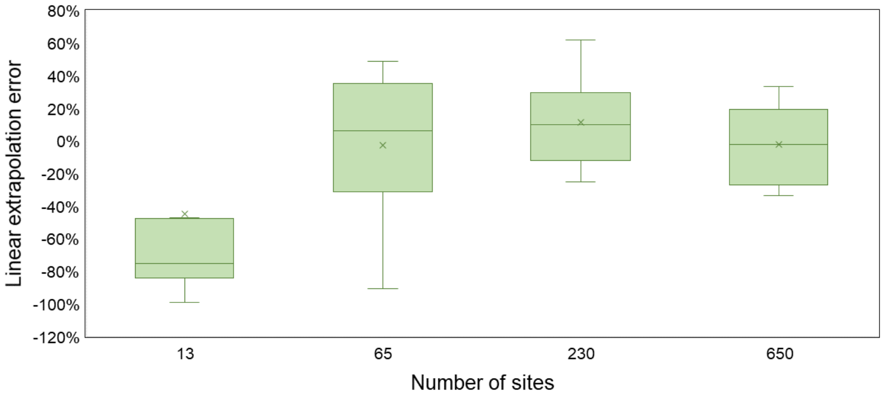
The Green River Basin case study focuses on assets for an operator in Wyoming with 1,254 simple well sites and 128 central delivery points. Each site has detailed activity and emission information at the source-level. The goal of this case study is to quantify spatial extrapolation error and understand the key variables to consider when selecting sample populations



Green River Basin case study

Extrapolation method impacts the uncertainty associated with spatial extrapolation. Increasing sample population size decreases spatial extrapolation error, though there is still variability in this trend





Green River Basin case study

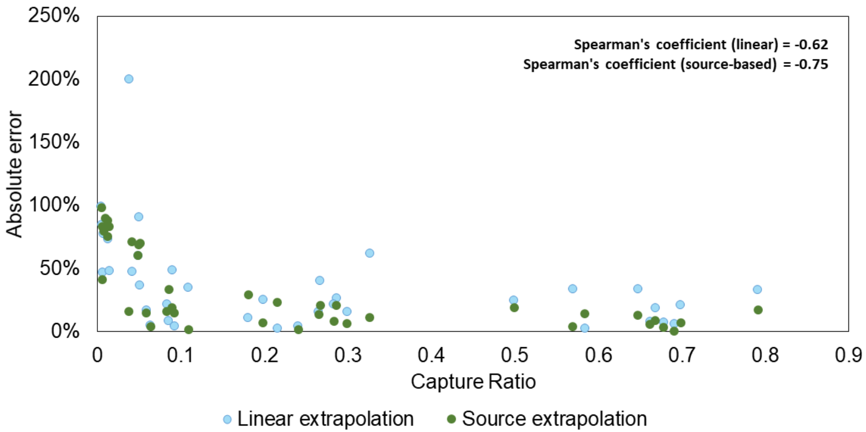
We hypothesized that the accuracy of a sample population in representing a larger region relied on the sample population capturing the behavior of the most complex sources. The capture ratio is a metric that quantifies how well each source type is represented, weighted by the skewness of the emission distribution of each source type

$$Skewness\ (G_{1,y}) = \frac{N_{y,total}}{(N_{y,total}-1)(N_{y,total}-2)} \sum \left(\frac{x_i - \bar{x}}{s}\right)^3$$

$$Capture\ Ratio = \frac{\sum_y^{all\ source\ types} G_{1,y} * \frac{N_{y,sample}}{N_{y,total}}}{\sum_y^{all\ source\ types} G_{1,y}}$$

Green River Basin case study

Spatial extrapolation uncertainty depends on the complexity, or skewness, of the source-level emission distribution, and how well these skewed emissions are represented in the sample population. Metrics that consider source-level behavior will be more applicable than sample population size alone



Importance of emission source behavior in measurement campaigns

Duration ratio informs sampling frequency to minimize temporal extrapolation uncertainty

Capture ratio informs sample population selection to minimize spatial extrapolation uncertainty

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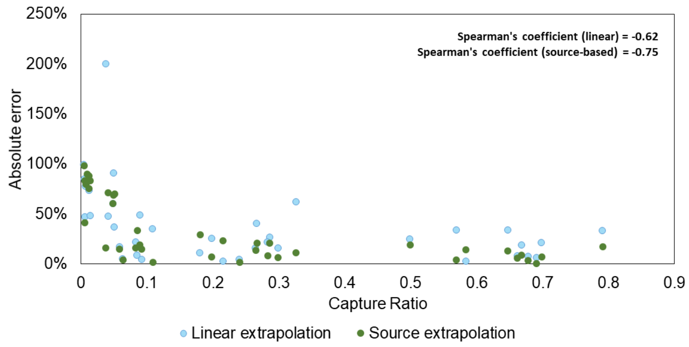

Main Takeaways

- Source level emissions characteristics such as distributions of magnitudes and durations are important for understanding expected variation between site and source level measurements, and for designing effective measurement campaigns
- Temporal and spatial extrapolation uncertainty should be considered when assessing emission inventory estimate uncertainty
- Extrapolation methods are important in understanding extrapolation uncertainty

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Thank you for listening!

Questions?

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Barnett Shale case study: Colette Schissel and David T. Allen
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